

Title: Spatial evaluation and trade-off analysis of soil functions through Bayesian networks.

Running title: Evaluation of soil functions with Bayesian networks.

Dirk Vrebos¹, Arwyn Jones², Emanuele Lugato², Lilian O'Sullivan³, Rogier Schulte⁴, Jan Staes¹ & Patrick Meire¹

¹Department of Biology, University of Antwerp, Antwerpen, Belgium

²European Commission, Joint Research Centre (JRC), Ispra, Italy

³Crops, Environment and Land Use Programme, Teagasc, Wexford, Ireland

⁴Wageningen University, Wageningen, The Netherlands

Corresponding author: Dirk Vrebos, +32 (0)32658719, dirk.vrebos@uantwerpen.be

Abstract

There is increasing recognition that soils fulfill many functions for society. Each soil can deliver a range of functions, but some soils are more effective at some functions than others due to their intrinsic properties. In this study we mapped four different soil functions on agricultural lands across the European Union. For each soil function, indicators were developed to evaluate their performance. To calculate the indicators and assess the interdependencies between the soil functions, data from continental long-term simulation with DayCent model were used to build crop specific Bayesian Networks. These Bayesian Networks were then used to calculate the soil function performance and trade-offs between the soil functions under current conditions. For each soil function the maximum potential was estimated across the European Union and changes in tradeoffs were assessed. By deriving current and potential soil function delivery from Bayesian networks a better understanding is gained on how different soil functions and their interdependencies can differ depending on soil, climate and management.

Keywords:

Bayesian modeling, DayCent, European Union, mapping, maximization, soil function, trade-offs,

Highlights

- When increasing a soil function, how do trade-offs affect the others under different conditions?

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- Bayesian networks evaluate trade-offs between soil functions and estimate their maximal delivery.
- Maximizing a soil function has varied effects on others depending on soil, climate and management.
- Differences in trade-offs make some locations more suitable to increase a soil function than others.

Abbreviations:

BN = Bayesian network, EU = European Union, JRC = Joint Research Council, N = Nitrogen, P = Phosphorus, C = Carbon, LUCAS = Land Use/Land Cover Area Frame Survey.

1. Introduction

In recent years, the scientific literature has devoted considerable attention to the concept of “soil ecosystem services” or “soil functions”. This interest stems from the increasing recognition that soils not only provide food and fiber but fulfill many other functions for society. (Adhikari & Hartemink, 2016; Baveye *et al.*, 2016). Haygarth and Ritz (2009) propose 18 soil based ecosystem services that include provisioning services such as water storage, regulating services such as gas regulation and cultural services embedded in heritage or recreational demands. While our dependence on soils and their functions for the provisioning of natural resources has long been overlooked (Gomiero, 2016), an increased environmental awareness has made the multi- functionality of soils progressively become a key feature in policy-making related to land use planning (Schulte *et al.*, 2014; Vrebos *et al.*, 2017). Demands exist for a wide range of soil functions, but vary greatly between countries and regions, as determined by population, land use, farming systems and livestock densities, geo-environmental conditions and landscape configuration (Schulte *et al.*, 2019). In most countries, agricultural land makes up large parts of the territory making these systems important suppliers of many soil functions.

Each type of soil has a certain potential or relative capacity to provide these functions. To a large extent this capacity is determined by inherent soil properties, environment and climate conditions (Vogel *et al.*, 2019). As a result, some soils are more effective at some functions than others (Schulte *et al.*, 2015). The actual function delivery is defined as this multitude of physical, chemical and biological processes interacting in soils which are affected by both climate and management (Schulte *et al.*, 2015; Vogel *et al.*, 2019). The different soil functions are often, partially interdependent because they share some of the soil processes and characteristics. Consequently, changes in land management (crop rotation, tillage practices, soil amendments) can affect multiple attributes and processes. Management changes to increase a particular soil function can simultaneously affect other soil functions in either positive or negative ways. Because of these trade-offs, a soil can never deliver its

entire potential for each soil function. Optimizing one soil function, such as primary productivity in agricultural land, will impact others, potentially reducing other vital soil functions. Understanding which soil functions can co-occur under different soil, climate and management conditions and which underlying soil processes are essential is a pertinent research topic that is being explored by many (Baveye, 2015). Understanding the associated trade-off mechanisms is crucial to obviate the unexpected and unintended consequences of policies on land-use and management. While each soil function can be optimized to its maximal potential, tradeoffs between these functions may occur, limiting the delivery of the other soil functions. For example, management aimed at maximizing primary production may inadvertently affect the 'water purification' or 'habitat' functions. This has led to conflicting management recommendations and policy initiatives on a European level.

Soil functions are conceptual constructs and although they can be defined, they are generally not measurable properties. They are considered to be essential assets emerging from a multitude of complex interactions between physical, chemical and biological processes in the soil (Vogel *et al.*, 2018). Despite an increase in soil function research, we still do not know how to directly measure most of these functions (Baveye *et al.*, 2016). As a solution to this problem, suitable indicators, which are derived from observable soil properties, have been proposed (Rutgers *et al.*, 2012). These indicators should be based on our understanding of how soil functions are generated through the complex interactions of soil processes and not only on pure statistical correlations (Bünemann *et al.*, 2018; Vogel *et al.*, 2019). In recent years, frameworks and methodologies have been developed to measure and monitor soil functions (Vogel *et al.*, 2018). But actual measured data, especially on large scales, e.g. the whole of Europe, is still missing (van Leeuwen *et al.*, 2017). As an alternative, results from process-based models can help us to better understand relationships between the potential of these soil processes and the actual soil function delivery through management. Yet it remains difficult to synthesize the mechanisms and patterns from such detailed models. The complexity of the results is often beyond our ability to understand and control, yet it is considered to be densely packed, ordered and structured in some way that we fail to comprehend as yet (Nowotny, 2005). Complexity reduction is needed to identify the most relevant mechanisms and patterns. Machine learning, a branch of computer science dealing with designing systems that can learn from data, can facilitate such complexity reduction. More specifically, Bayesian Belief Networks (BN's) are well-suited to integrate complexity and incomplete knowledge, which are common in ecological systems and soils (Landuyt *et al.*, 2013).

Bayesian networks (BNs) are a graphical representation of joint probability distributions (Pearl, 1988), where model outputs are probabilities calculated using Bayes' Theorem (Marcot & Penman, 2019). As networks, they can cope effectively with incomplete information on the relationships between variables, thus facilitating modelling when data availability is insufficient to render a deterministic approach feasible. In recent years BNs have been used in soil science for up scaling empirical observations to predict soil properties over larger areas (Bogaert & D'Or, 2002; Kaye *et al.*, 2008) or to better understand complex interaction between management and pedo-climatic factors when

evaluating soil properties (Dal Ferro *et al.*, 2018). BNs are increasingly integrated with spatial datasets to map soil properties, soil functions and ecosystem services (Van der Biest *et al.*, 2014; Smith *et al.*, 2018; Grafius *et al.*, 2019). By using BNs, predictions can still be made for combinations of soil properties where not all information is available, improving the mapping, while taking uncertainties regarding missing information into account. Therefore, BNs, are very suitable to predict soil function potentials and associated trade-offs towards the other soil functions on larger scales.

For this study we build on the concept of functional land management as was developed by Schulte *et al.* (2011). This study assesses four out of five soil functions given by Schulte *et al.* (2011) and Bouma *et al.* (2012) as they are specifically adapted towards agricultural soils:

- Production of food, fiber and (bio)fuel: traditionally the soil function that provides a livelihood to farmers and associated sectors in the rural environment;
- Water purification and regulation: the ability of soils to purify (quality) and regulate (quantity) water for human consumption and maintenance of ecosystem integrity;
- Carbon sequestration and climate regulation: the ability of soils to store organic carbon for (a) partial offsetting of GHG emissions and (b) regulation of biological and physical soil processes
- Recycling of (external) nutrients/agro-chemicals; specifically, the ability of soils to provide a sustainable receptor for external nutrients such as those derived from landless farming systems (e.g., pig and poultry farms), as well as sewage sludge and other organic waste products.

We used machine learning to develop crop specific BNs. To learn the network, we used data from a long-term simulation at EU level, in which the DayCent biogeochemical model was applied over soil sampling locations of the Land Use/Land Cover Area Frame Survey (LUCAS). The initial network was validated with expert input to retain only plausible relationships within the network. The resulting BN's are able to calculate a predicted supply of the soil functions for a suite of input combinations. Performance indicators were developed, which allow the interdependencies between the soil functions to be evaluated. These BNs were then used to map and evaluate the soil function performance on agricultural land across the EU under current conditions. For each soil function the maximum potential was estimated across the EU and changes in tradeoffs were assessed. The presented results help to better understand how different soil functions and their interdependencies can differ depending on soil, climate and management.

2. Methodology

2.1. DayCent dataset

DayCent, the daily time-step version of the CENTURY biogeochemical model, simulates fluxes of carbon (C) and nitrogen (N) among the atmosphere, vegetation, and soil. It incorporates a wide range of sub models including soil water content and temperature by layer, plant production and allocation of net primary production (NPP), etc. (Parton *et al.*, 1998). The JRC applies this model at the EU scale on the LUCAS sample points (Ballabio *et al.*, 2016; Orgiazzi *et al.*, 2018), to estimate carbon dioxide (CO₂) and nitrous oxide (N₂O) emissions in agricultural soils under different scenarios (Lugato *et al.*, 2017; Lugato *et al.*, 2018; Quemada *et al.*, 2020) and is validated for these two parameters. The DayCent model was applied on a 12-year simulation period following the procedure in Lugato *et al.* (2017). More information on the models setup, validation and associated uncertainties can be found in that publication. In total, about 12.000 point classified as arable and grassland were simulated.

From this simulation only the last 4-years of the model run were used to develop the data table for the machine learning. The daily time-step output from DayCent was converted into a data table with seasonal and yearly averages and totals. This table includes a wide range of explaining variables from DayCent (Table 1). In total 14 indicators were derived from the DayCent modelling results to describe different aspects of the four soil functions. A description of these 14 indicators can be found in Addendum A. Of these 14, six indicators were further used in the analysis (see 2.2). The final data table contained 67,144 data points for 15 different crops. This dataset was used to derive soil function indicators and create the crop specific BNs.

2.2. Soil function indicators

Generally, soil functions are estimated based on observable soil attributes which are used as indicators (Vogel *et al.*, 2019). The use of modelled indicators for soil functions is less common, but allows a quantitative evaluation (and assessment of trade-offs).

For each of the soil functions one indicator was selected from the 14 available soil indicators to estimate the soil function performance. Only for “water purification and regulation” multiple indicators were used, as it was impossible to incorporate all relevant aspects of this function into one single indicator. Indicators for “water purification” and “nutrient cycling” only cover one aspect, nitrogen, of the soil function. Each indicator is developed in such a way that high values indicate a positive, high soil function performance.

- Primary Productivity (PP) - Primary yield (g C / (m² * year)). This indicator gives an estimation of the net total harvest for the different crops. The indicator thus gives an estimation of how productive the soil is under local conditions and will increase or decrease with changes in these conditions.
- Climate regulation (CR) – total CO₂-equivalent of greenhouse gas emissions (g C / (m² * year)). The indicator includes the combined effect of carbon sequestration or emission from the passive soil carbon pool and N₂O emissions from the soil. Out of the three soil carbon pools available in DayCent only the passive pool is used, as this pool stores C for a long period of time.

- Water regulation: drought (DR) – daily drought indicator (days / year) (ratio). The drought indicator estimates the number of days per year that plants are not in drought stress condition. Drought stress conditions are present when the ratio between actual evapotranspiration and potential evapotranspiration is less than 0.5.
- Water regulation: water logging (WL) – daily no water logging (days / year) (ratio). To estimate the impact of too wet soils, the number of days the soil is not waterlogged is calculated as the number of days per year that the deepest soil layer is not draining to the subsoil, 30 cm deep.
- Water purification (WP) – Nitrogen leaching compared to Nitrogen inputs (ratio). The indicator quantifies the relative portion of N that is released to the ground water compared to the amount of nitrogen (N) inputs provided to the soil through different pathways (fertilizer application, atmospheric deposition and biogenic N-fixation). The indicator signifies the ability of the soil to retain or remove N and prevent it from entering the ground water layers. Absolute N load would give a value for N loss from the landscape. However, it does not give information about a particular soil relative to another. Therefore a ratio was used as it enables a relative comparison on the capacity of the soil to deliver water purification that is not confounded by the scale, wide ranges in management, edaphic or ecological factors.
- Nutrient cycling (NC) – Nutrient use efficiency (ratio). The efficiency of the soil's nutrient cycling is given as the actual nutrient use efficiency. The relative amount of N that is harvested compared to the amount of nitrogen that is provided to the soil through different pathways. It signifies the soil's ability to recycle the applied nitrogen into harvestable products.

Some of the soil function indicators, such as for “nutrient cycling” combine different properties. The performance of this indicator can be influenced by both changes in harvest and in N provisioning. When optimizing the function, it is not automatically clear which of these factors determine the changes in functioning. Therefore, additional DayCent outputs were included in the Bayesian modelling to allow for a better interpretation of the modelling results.

2.3. Bayesian network development

A Bayesian network is a probabilistic graphical model which represents a number of variables and their conditional dependencies through a directed acyclic graph. To develop the BNs, each explaining variable and soil function indicator from the data table, which was derived from the DayCent dataset, was discretized into 5 classes using the Jenks natural breaks classification method (Jenks, 1967). Defining class breaks was done by seeking to minimize each class's average deviation from the class mean, while maximizing each class's deviation from the means of the other groups, thereby reducing in-class variance and increasing the comparability of multiple maps.

For each crop, a BN was derived from these discretized datasets with a Bayesian Search algorithm (Cooper & Herskovits, 1992; Heckerman *et al.*, 1995). The number of iterations was set at 10% of the number of available DayCent data points, while for each iteration 2% of the DayCent data points was used. During the Bayesian Search calculation, connections between explaining variables were

forbidden, while connections between explaining variables and soil function variables were always starting from the explaining variables. The Bayesian search algorithm was allowed to search for statistical relationships in between the soil function indicators, but these were reviewed by experts. Connections which were found by the Bayesian search algorithm, but could not be linked to a known physical, microbial or other functional process were forbidden in a subsequent rebuild of the BN's. An overview of these connections is given in Addendum A.

The crop BNs were validated with a k-fold cross-validation (Stone, 1974) during which the network is tested in its ability to predict indicator values from the dataset. During this validation the available dataset is divided into K parts of equal size, the network is trained on $K-1$ parts, and tested on the last, K^{th} part. From the K^{th} part, input variables are set in the BN and the BN predictions of the soil function indicators are compared with the soil indicator predictions in DayCent data table. The accuracy for each soil function indicator is calculated as the proportion of correct predictions. The same number of iterations (k-parts) was used during the cross-validation as during the development of the BNs. The BNs were built and validated using SMILE Academic 2.2 software (BayesFusion LLC, University of Pittsburgh, PA, USA) (Druzdzal, 1999).

2.4.Spatial analysis

In a first step, maps and spatial databases that provide relevant information for the input parameters were collected (Table 2). Most of this information was directly converted to the same units as the BN variables and a resolution with a pixel size of 1km X 1km. Spatial data on crop distribution required a more advanced pre-processing. The CORINE land cover maps only provide spatial information in a coarse thematic resolution (e.g. complex cultivation patterns). On the other hand, the Spatial Homogeneous Mapping Unit database (HSMU) provides a specific number of hectares (ha) for each crop within one HSMU (Leip *et al.*, 2008). The HSMU units can range in size between a few m² up to several hundred km². To overcome this difference in information detail, information from both CORINE and the HSMU database were combined. For each pixel within a HSMU, which was specified in CORINE as agricultural land, a particular crop and its BN was randomly selected, while taking into account the prevalence of the different crops within that HSMU. This selection was done with the random.choice function in Python/NumPy (version 1.16.4). After the crop BN was selected, all other spatial information was provided to the BN.

Although the DayCent dataset incorporates a large number of sample points and associated combinations of explaining variables, not all possible combinations of soil, environment and management classes were covered by the LUCAS data points. For these combinations the crop BNs cannot give direct estimates of the soil functions. For locations with such non-existing combinations, the missing input parameters with the least predictive power was iteratively removed until an existing combination (for the remaining parameters) is found in the BN. This predictive power of the explaining variables within each BN was derived through a strength of influence analysis in the GENIE program

(BayesFusion, 2018). The BN was then able to give a prediction based on available information, but with a higher, unknown, uncertainty.

For each soil function indicator, the probabilities for each state were derived from the updated BN. This information was then translated into a single map by multiplying these probabilities with the mean value of the respective state and adding them up to one overall value for each pixel.

Maximizing the soil functions was done for each pixel by applying the same crop BN and most of the spatial information from the current soil functioning mapping. Information on management practices was not applied in the BN to leave this open for the BN to search for optimal practices. For each soil function indicator an iterative procedure was applied in which the maximum soil function performance was searched for in the BN. To do so, a list with possible probability combinations was created where all combinations over the five states with a 0.1 step was compiled: [1,0,0,0,0], [0.9,0.1,0,0,0], [0.8,0.1,0.1,0,0], ... For each combination, mean soil function values were calculated = \sum (probability of a state X mean value of a state). After which the list with combinations was sorted from highest soil function value to lowest. Each combination was tested in the BN in consecutive order, until a combination of probabilities met the following conditions:

- The BN had to be able to fit the management variables with the local soil and environmental properties and the requested soil function probabilities.
- The states used by a combination of probabilities had to be supported by at least 5% of the data points within the DayCent dataset which had the same crop and explaining variables. This condition was used to make sure that the outcome was not based on outliers, e.g. when the information for the highest state was provided by only one data point, but supported by robust evidence.

Again for each soil function indicator, the probabilities of each state were derived from the updated BN and converted to a single value for each pixel.

2.5. Statistics

To better understand the relationships between the different soil functions on different scales, smaller environmental zones compared to the EU, the soil function maps with the mean values were randomly sampled ($n = 200,000$). This dataset was tested for normality following the Shapiro-Wilk test and where needed parameters were transformed following the formula:

$$T(x) = \text{sign}(x) * \log(|x| + 1)$$

Pearson correlations were calculated between the different soil function indicators. As soil functions are defined by both soil and climate, spatial variation can be expected and relationships between these soil functions might differ between regions. Pearson correlations were calculated and compared at the level of the environmental regions of Europe, which were derived from climatic, geomorphological and soil data (Metzger *et al.*, 2005; Jongman *et al.*, 2006).

To estimate the effect of soil function maximization, the same sample points were used to sample the outcome maps of the maximization calculations and the same statistical procedure was applied. All statistics were done in R version 3.5.1 (R Core Team, 2018).

To compare the change in supply of the different soil functions, the dataset was transformed into z-scores. In this way a comparison could be made between scenarios, indicators with different units and both positive and negative indicator values. These z-scores give the signed fractional number of standard deviations by which the value of one of the random sample points are above or below the mean value and allow us indicate which areas have a higher or lower soil function performance compared to the mean value. To make an evaluation of the change in supply possible, z-scores for the maximization scenarios were calculated with the mean values and standard deviations of the current soil function supply.

3. Results

3.1. Bayesian networks

For each of the 15 crops, a unique Bayesian network was developed (Vrebos *et al.*, 2020; <https://doi.org/10.15454/YA4OSH>). The number of available data points differed between crops as some occur more frequently, or over larger areas. The number of selected explaining variables within one BN ranged between 11 and 18 variables. All of the 21 explaining variables, available in the data tables, were selected in at least one of the Bayesian networks. While no connections were allowed between the explaining variables, each BN contained several connections in between the soil function variables. The example of the grain maize BN is given in Figure 1. All BNs can be found in Addendum A.

K-fold cross-validation was done for the different BNs. Accuracy differed between soil functions and crops. Most of the values ranged between 0.5 and 0.75. Overall prediction of the climate regulation indicators performed best (Table 3). The largest differences are found for PP, where some of the BNs have low accuracy in prediction including the wheat (0.31) and the rapeseed (0.36) BNs. Overall the BNs give reliable predictions for the different soil functions.

3.2. Current soil functions

Evaluation of the current supply of the soil functions demonstrates the spatial variation of each soil function throughout the EU. Figure 2 shows the detail for each of these maps for part of The Netherlands. Soil function performance varies greatly across short distances, partly due to differences in crops, but also because of soil and climate characteristics. For each soil function, there are distinct patterns. For many countries, a high primary productivity corresponds with a lower performance for the other soil functions. The direction and strength of these trade-offs does however vary between countries as influenced by soil and environmental characteristics. The full maps can be found in Addendum B.

The magnitude of soil functions provided differs between croplands and grasslands. Croplands have a higher primary productivity, nutrient cycling and water purification. As they take up more nutrients, under appropriate management, they cycle and remove nitrogen more efficiently. Grasslands have a higher climate regulation capacity and are more drought resilient.

Pearson correlations between the soil functions differ strongly (Figure 3). None of the soil function indicators is positively or negatively correlated with all other soil functions. Primary productivity is only positively related with nutrient cycling. Water purification has a positive correlation with four out of five of the other soil functions. While the strength of these correlations differ, all of them give an overall statistical significant result.

Although the directions of most relationships between soil functions are stable across the EU, some correlations can differ compared to the overall EU trends and between environmental zones. For example, climate regulation and water purification are negatively correlated for the Atlantic North, while this is not the case for the other environmental zones. In the Mediterranean North, primary productivity and nutrient cycling are negatively correlated, while this is not consistent with the EU trend which is positive in most other zones (Figure 3 and 4). Although the direction of most relationship remains the same, the strength does vary. Rho-values for the Atlantic Central are stronger than those found for the Mediterranean South.

3.3.Trade-off analysis

According to the BNs, the delivery of each of the soil functions can be significantly increased by altering the management parameters, however not all to the same extent (Figure 5). Water purification can only be increased in a limited way, while waterlogging regulation can increase significantly. But maximizing exclusively one soil function, inherently affects the other soil functions.

Targeting one of the soil functions specifically, does not only change that soil function, but also elicits a change in other soil functions owing to the relationships between them (Figure 6). When optimizing for primary productivity, the rho values between the primary productivity and the other soil functions remain almost the same. However, some of the relationships between the other soil functions do change. For example, water purification and climate regulation become negatively correlated, while this used to be positive under current management. After maximizing for climate regulation, the same change between climate regulation and water purification can be found, but also the relationship between primary productivity becomes positive as well as others.

4. Discussion

Soils are a key resource and simultaneously deliver different functions to society. Notwithstanding certain knowledge gaps, there is vast scientific research to describe individual soil processes and functions. The complexity of integrating such research to better understand soil multi-functionality including the trade-offs and synergies between soil functions means that understanding how these

functions vary across different scales and how they relate to each other, remains a persistent challenge. In this study, an integrated approach to capture the relationships between four key soil functions was investigated. Unlike many other studies that use field measurements, modeling results were used to develop and calculate the soil function indicators. As a result, indicator values could be calculated for a large area and indicators could be developed from data which are difficult to measure, especially on many different locations. Model results also incorporate additional levels of uncertainties, compared to measured data. Importantly, the DayCent model was developed in the first instance to simulate fluxes of carbon and nitrogen and as such, submodules regarding these fluxes are more detailed and more accurate than those which calculate for example the water dynamics and primary productivity. Therefore, outcomes for the soil function “Carbon sequestration and climate regulation” can expect to be more reliable than those regarding “water regulation” as reflected in the higher predictive performance of BNs (Table 3). The available submodules also limited the number of available soil function indicators. For water purification’ and ‘nutrient cycling’ we could only assess the effects on nitrogen cycling., which only covers a limited part of the overall soil function.

By deriving Bayesian networks out of the datasets the most important connections between the different soil functions become apparent for each crop. These connections differ between crops. Part of this differentiation can be related to crop characteristics such as growth season, water use, nutrient requirements, etc. but to some extent also significant statistical relationships which have no direct mechanistic relationship. Untangling both types of variation remains a challenge, but our review of the networks was able to remove most of these effects where machine learning complexity reduction techniques could not be explained by domain experts. Overall the Bayesian networks are able to give a good prediction of the different soil functions. The explaining variables used in the analysis were able to explain a large part of the observed variation in soil functioning as given by the indicators. Some of the crop Bayesian models, such as potatoes, have a lower predictive value for primary productivity. Why this occurs is not clear and could require further investigation. Potentially data inputs, for example, the temperature and rainfall variables may not give the correct information to derive a good prediction of the growing season. To overcome this limitation in part and to better understand the observed changes in functionality, the Bayesian networks incorporated more than one indicator for each of the soil functions.

Our evaluation of the current supply of soil functions shows that there are not only significant differences within the EU between countries and ecoregions (macro-scale), but also that the spatial variation within regions can be very large. As indicated by many other studies (e.g. (Klapwijk *et al.*, 2014), we can conclude that an increased primary productivity is accompanied by a loss of performance for the other soil functions (Fig. 6). In regions with the highest primary productivity, we observe a lower performance for the other soil functions. But these are regional averages and our results also show that the direction and strength of these trade-offs are non-linear as they are influenced by local soil and environmental characteristics. Although the direction of many of these trade-offs are the same for all environmental zones, the strength in the relationships between soil

functions differs between environmental zone. This provides insight into the intensity of the trade-off and in turn could inform the intensity of management that might be required. There is also some variation in the direction in some of the trade-offs. To some extent, the model offers insights that may be important for regional policy targeting. Importantly, by identifying the direction of trade-offs, the methods developed here have scope to reduce future perverse policy outcomes, even if more research is needed to understand the most important driving forces in this variation. We have to acknowledge that EU-wide data on soil parameters, crops and management is rather coarse. The 1km X 1km resolution of our maps is appropriate for EU wide evaluations, especially because the basic data sources would not allow for greater spatial differentiation. It is also evident that soil parameters would display a high variety within a square kilometer. However, a similar approach applied at more data-rich regional scales, could be very informative to design national schemes and rural development plans that minimize these trade-offs by taking into account the intrinsic properties of the local environment and the potential supply of soil functions.

The interdependencies between the soil functions ensure that changes in crops and management regimes to maximize one soil function, not only affect the targeted soil function, but also the other soil functions considerably. Maximizing one soil function, always affects the other soil functions. The direction and magnitude of this can vary, again depending on local conditions. In many cases these changes do not affect the overall direction of the relationship between two soil functions. But under each maximization scenario at least some of these relationships change from positive to negative or the other way around. By altering management, the overall relationship between soil functions can turn around. These changes can have profound impacts on policy targets. Management actions from one policy domain are generally designed to improve a specific soil function. But these actions will also impact other soil functions, potentially compromising other policy aims and targets from other sectors. In addition, this requires understanding the cause-effect relationships which requires a detailed knowledge of the interaction between physical, chemical and biological processes driving these soil functions, but also the Bayesian networks behavior itself. For example, the relationship between primary productivity and climate regulation becomes positive when the climate regulation function is maximized. But when we maximize primary productivity, there is no positive effect on climate regulation. To improve climate change regulation, reductions in N₂O need to be realized. This can be done by reducing N-fertilizer, but also by improving conditions which will promote plant growth, nutrient uptake and primary productivity, which decreases the amount of residual nitrogen for bacterial activity and associated N₂O emissions. Improving primary productivity is mostly done by increasing N-fertilization. Not all of this nitrogen is taken up by crops, making them available for bacterial activity and associated N₂O emissions. Understanding these cause-effect relationships is relevant to design effective policy and management. However, the growing urgency to redress environmental degradation and manage agriculture for both production and environmental goals insists that interventions must better account for the policy impact across policies, so that policy aims and targets across sectors are not compromised. It is also true that there is a strong variability on the

demands for each of these soil functions previously described by Schulte *et al.* (2019), which must be considered in pursuit of a more sustainable land base for Europe.

5. Conclusions

The supply of soil functions varies regionally due to soil, environment and management with the maximization of individual soil functions highlighting different patterns of impact for other soil functions. Overall, exploiting in favor of one soil function generally induces a negative effect in many cases. In this research, we have developed a mechanism that has scope to support more integrated policy design to reduce the likelihood for trade-offs to occur.

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Conflict of Interest Statement

There are no potential conflicts to be reported.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Authorship

Study concept and design: Vrebo, Jones, O'Sullivan, Schulte and Staes. DayCent modelling: Lugato and Jones. Analysis and interpretation of data: Vrebo and Staes. Drafting of the manuscript: Vrebo. Critical revision of the manuscript for important intellectual content: Jones, Lugato, O'Sullivan, Schulte, Staes and Meire. Statistical analysis: Vrebo.

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Figures

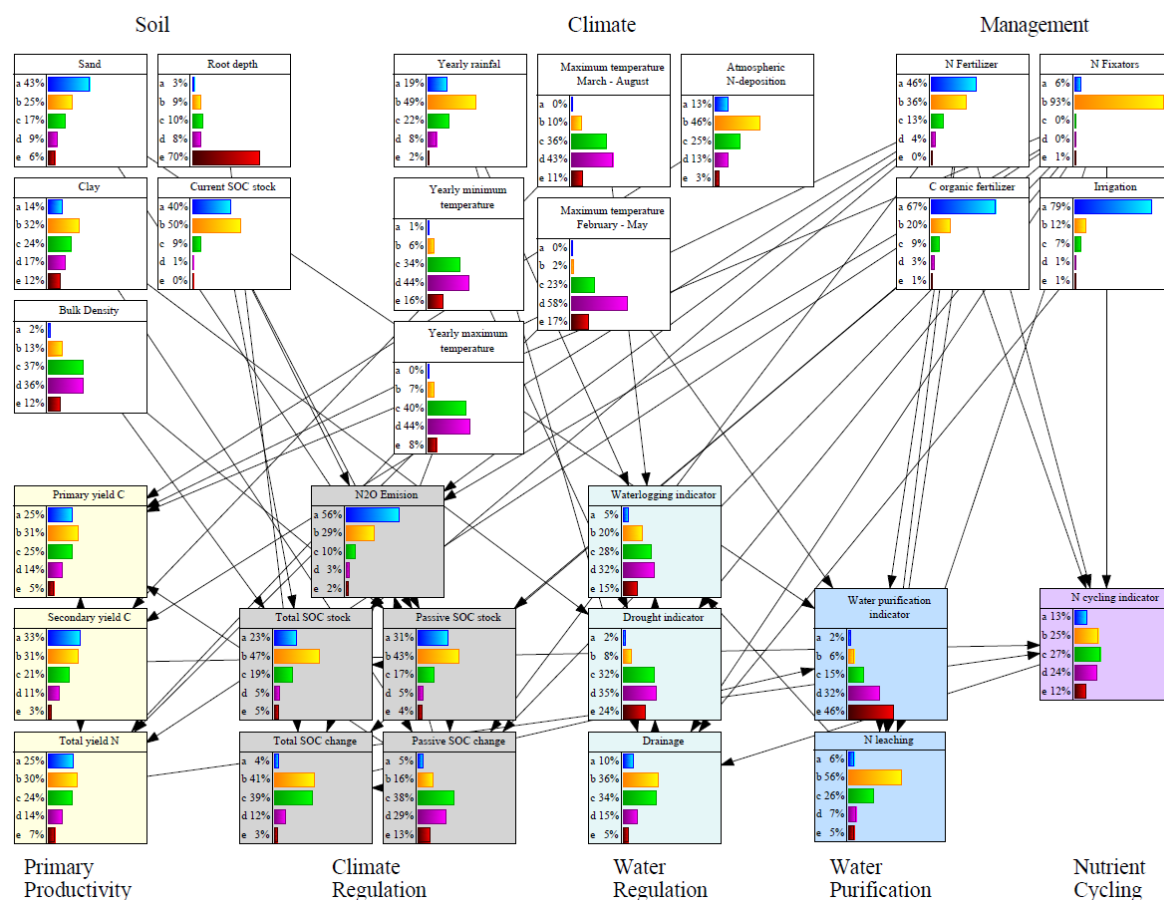


Figure 1: Acyclic directed graphs (DAC) of the BN for grain maize with the probability distribution. Explaining variables (white) are grouped according to their characteristics in the upper part of the graph, soil function variables and indicators are grouped according to the soil functions in the lower part.

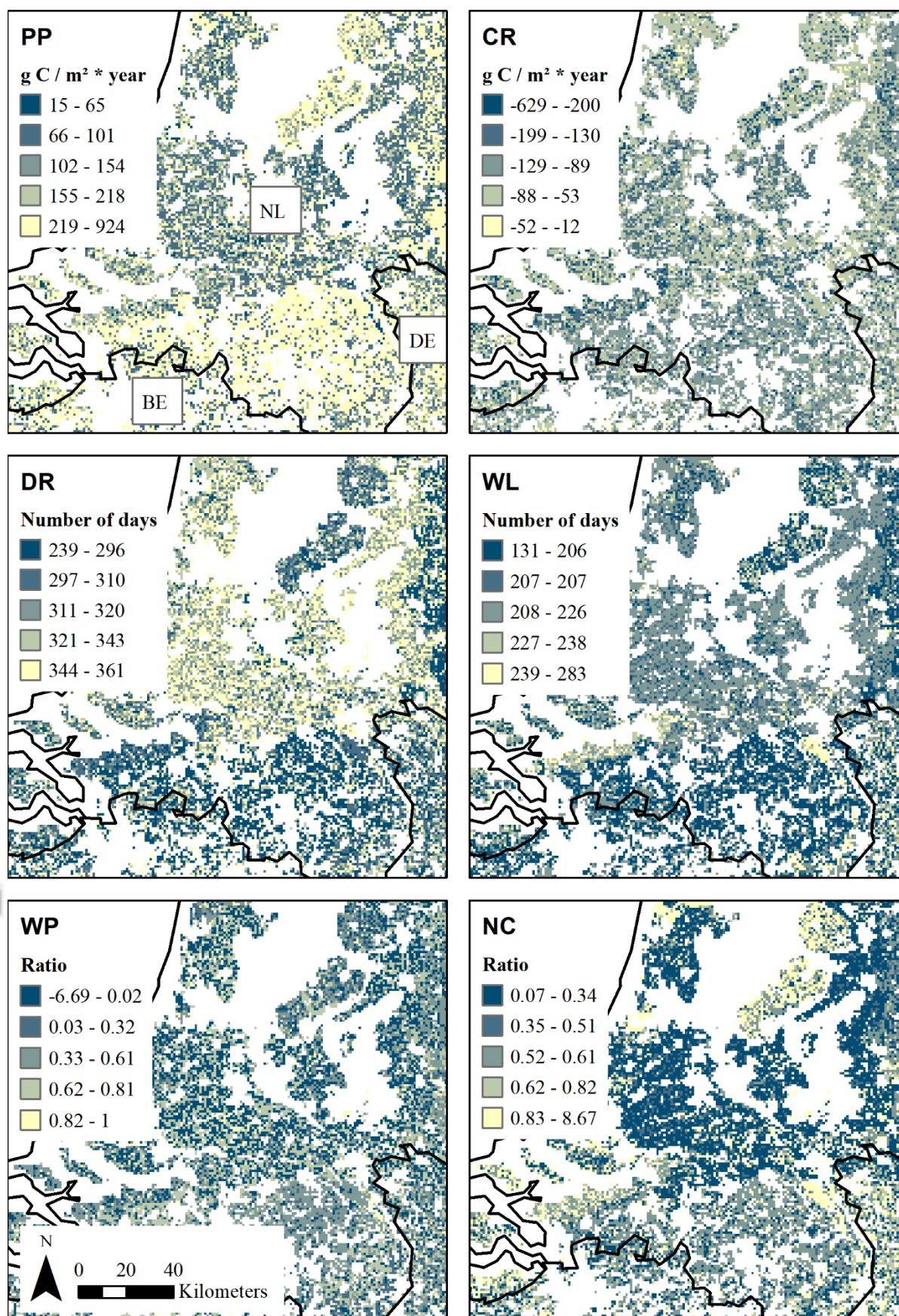


Figure 2: Detail of the different soil function maps: PP = Primary productivity, CR = Climate regulation, DR = Water regulation – drought protection, WL = Water regulation – waterlogging protection, WP = Water purification, NC = Nutrient cycling. NL = The Netherlands, BE = Belgium, DE = Germany. Legends are non-linear and based on quantiles to better illustrate the spatial variation.

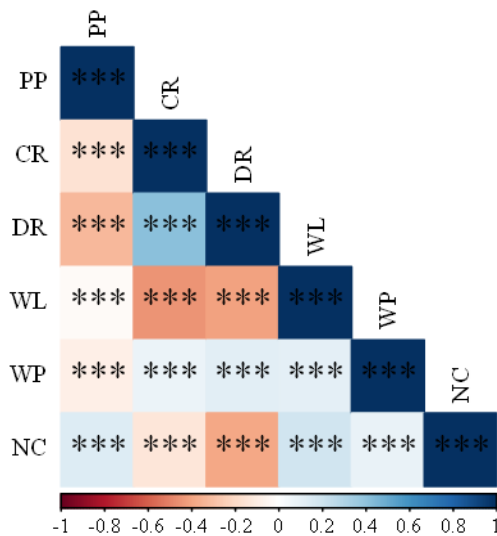


Figure 3: Correlation matrix of Pearson correlations between the different soil function indicators for the entire European Union (n = 200 000). PP = Primary productivity, CR = Climate regulation, DR = Water regulation – drought protection, WL = Water regulation – waterlogging protection, WP = Water purification, NC = Nutrient cycling. (relationship strength and direction provided in color bar with Pearson r, * = p-value < 0.05, ** = p-value < 0.01, *** = p-value < 0.001).

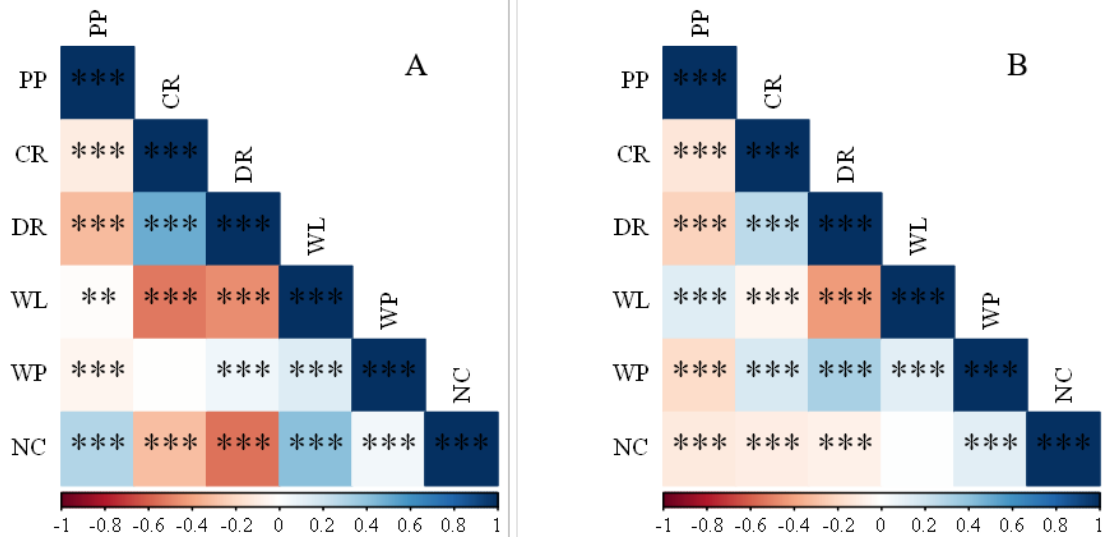


Figure 4: Correlation matrix of Pearson correlations between soil function indicators for two environmental zones A = Atlantic Central (n = 39 394), B = Mediterranean North (n = 6 748). PP = Primary productivity, CR = Climate regulation, DR =

= Water regulation – drought protection, WR = Water regulation – waterlogging protection, WP = Water purification, NC = Nutrient cycling. (relationship strength and direction provided in color bar with Pearson r , * = p-value < 0.05, ** = p-value < 0.01, *** = p-value < 0.001).

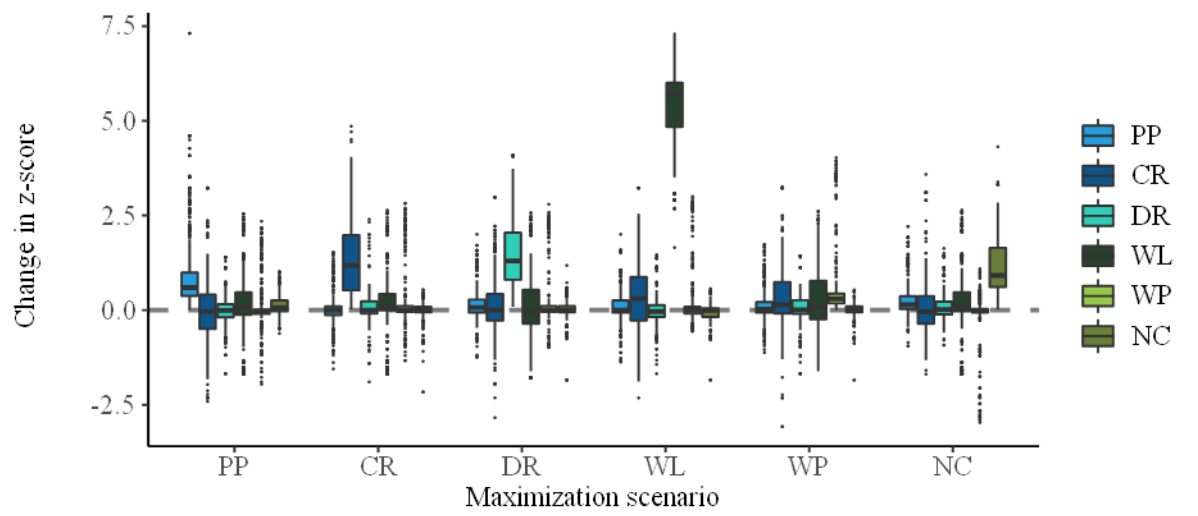


Figure 5: Boxplot of the range in changes in soil function supply for the different maximization scenarios ($n = 200,000$). PP = Primary productivity, CR = Climate regulation, DR = Water regulation – drought protection, WR = Water regulation – waterlogging protection, WP = Water purification, NC = Nutrient cycling. Mean, median and standard deviations are given in Addendum C.

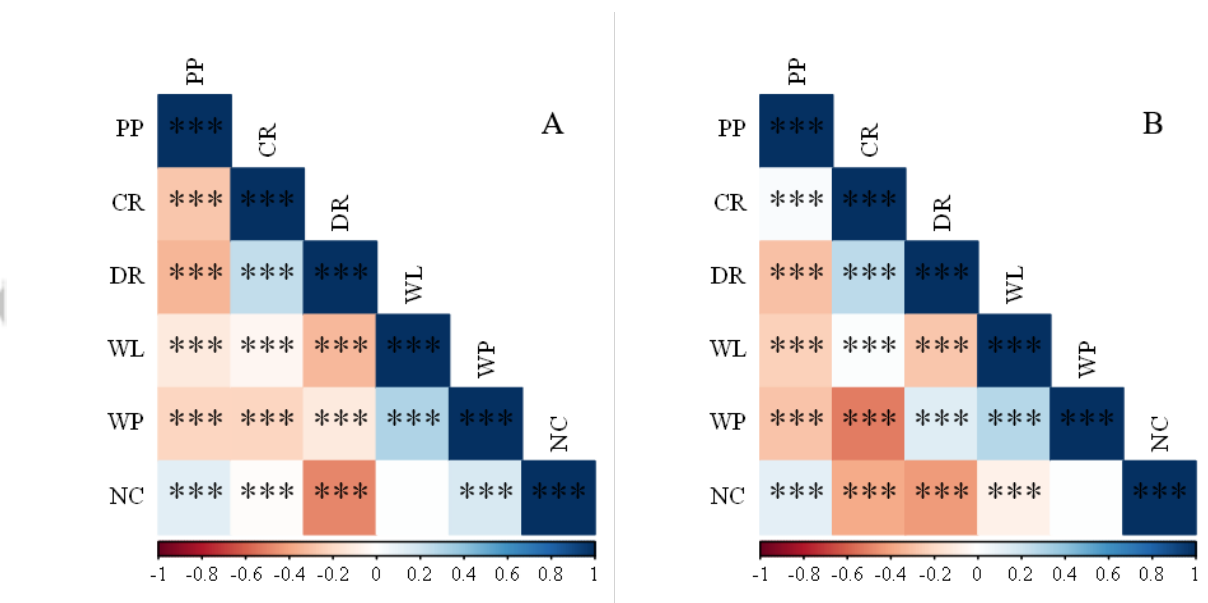


Figure 6: Correlation matrix of Pearson correlations between soil function indicators for two maximization scenarios A) Primary Productivity and B) Climate regulation. PP = Primary productivity, CR = Climate regulation, DR = Water regulation – drought protection, WR = Water regulation – waterlogging protection, WP = Water purification, NC =

Nutrient cycling. (relationship strength and direction provided in color bar with Pearson r , * = p-value < 0.05, ** = p-value < 0.01, *** = p-value < 0.001).

Tables

Table 1: Overview of the explaining variables used to develop the Bayesian networks.

Soil		Environment	
Parameter	Unit	Parameter	Unit
Sand	%	Yearly minimum temperature	°C
Clay	%	Yearly maximum temperature	°C
pH (CaCl)		Total yearly rainfall	mm
Cation exchange capacity	meq/100 g	Minimum temperature March - May	°C
Rooting depth	cm	Maximum temperature March - May	°C
Bulk density	g cm ⁻³	Total rainfall March - May	mm
Current SOC	g C / m ²	Minimum temperature March - August	°C
		Maximum temperature March - August	°C
Management		Total rainfall March - August	mm
Parameter	Unit	Atmospheric N-deposition	g N / m ² * year
N in Fertilizer	g N / m ² * year		
C in Organic Fertilizer	g C / m ² * year		
N Fixation	g N / m ² * year		
Irrigation	mm / year		

Table 2: Overview of the different datasets used to map and maximize the soil functions. Units of the original maps are given.

Group	Variable	Dataset	Unit	Reference
Soil	Sand	Topsoil physical properties for Europe (based on LUCAS topsoil data)	%	Ballabio <i>et al.</i> (2016)
	Clay			
	Bulk density		g cm ⁻³	Ballabio <i>et al.</i> (2016)
	pH			Ballabio <i>et al.</i> (2016)
	Cation exchange capacity	European Soil Database v2 Raster Library 1kmx1km		Panagos (2006)
	Rooting depth	European Soil Database Derived data	cm	Hiederer (2013)
	Current SOC	Soil Organic Carbon (SOC) Projections for Europe	ton C / ha	Yigini and Panagos (2016)
Environment	Rainfall and temperature	E-OBS gridded dataset v19.0e averaged values 2008 – 2017	mm / year	Cornes <i>et al.</i> (2018)
	N-deposition	EMEP database, based on data from MET Norway - averaged values 2013 – 2017	kg N/ha	Simpson <i>et al.</i> (2012)

Management	Crop type	Corine Land Cover 2012 raster data V18 Spatial Homogeneous Mapping Unit database	Land use classes % crop within an HSMU	EEA (2016) Leip <i>et al.</i> (2008)
	N fertilizer C organic fertilizer N fixation	Spatial Homogeneous Mapping Unit database	ton N/ha or ton C/ha	Leip <i>et al.</i> (2008)
	Irrigation	Corine Land Cover 2012 raster data V18	mm / year	EEA (2016)

Table 3: Overview of the different crops, number of data points (n) and the accuracy (proportion of correct predictions) of each soil function indicator according to the K-cross validation. PP = Primary productivity, CR = Climate regulation, DR = Water regulation – drought protection, WR = Water regulation – waterlogging protection, WP = Water purification, NC = Nutrient cycling.

Crop	n	PP	CR Change passive SOC	N ₂ O emissions	DR	WL	WP	NC
Barley	27317	0.48	0.68	0.73	0.56	0.62	0.56	0.48
Silage maize	11080	0.61	0.59	0.72	0.55	0.54	0.63	0.42
Grain maize	6648	0.52	0.71	0.78	0.62	0.54	0.51	0.56
Intensive grasslands - hay	24339	0.67	0.62	0.76	0.54	0.58	0.83	0.74
Intensive grasslands - grazed	24339	0.55	0.61	0.77	0.52	0.56	0.56	0.77
Extensive grasslands - grazed	24339	0.74	0.66	0.78	0.56	0.57	-	-
Rapeseed	10966	0.36	0.64	0.64	0.50	0.54	0.50	0.55
Peas	1494	0.72	0.66	0.73	0.64	0.67	0.74	0.59
Potato	2844	0.36	0.77	0.89	0.61	0.62	0.61	0.63
Rye	2620	0.51	0.60	0.65	0.49	0.62	0.56	0.65
Sugar beet	2612	0.68	0.70	0.75	0.76	0.48	0.49	0.69
Sunflower	8002	0.51	0.63	0.82	0.56	0.48	0.65	0.50
Spring wheat	520	0.56	0.76	0.79	0.67	0.63	0.66	0.61
Spring durum wheat	430	0.51	0.48	0.81	0.55	0.53	0.97	0.54
Soybean	140	0.54	0.29	0.60	0.69	0.55	0.81	0.60
Wheat	22010	0.31	0.73	0.70	0.62	0.59	0.60	0.45
Durum wheat	3912	0.46	0.57	0.65	0.42	0.44	0.60	0.48

Addendum A: Bayesian networks for the different crops

Soil indicators

Overview of the soil indicators used in the BNs.

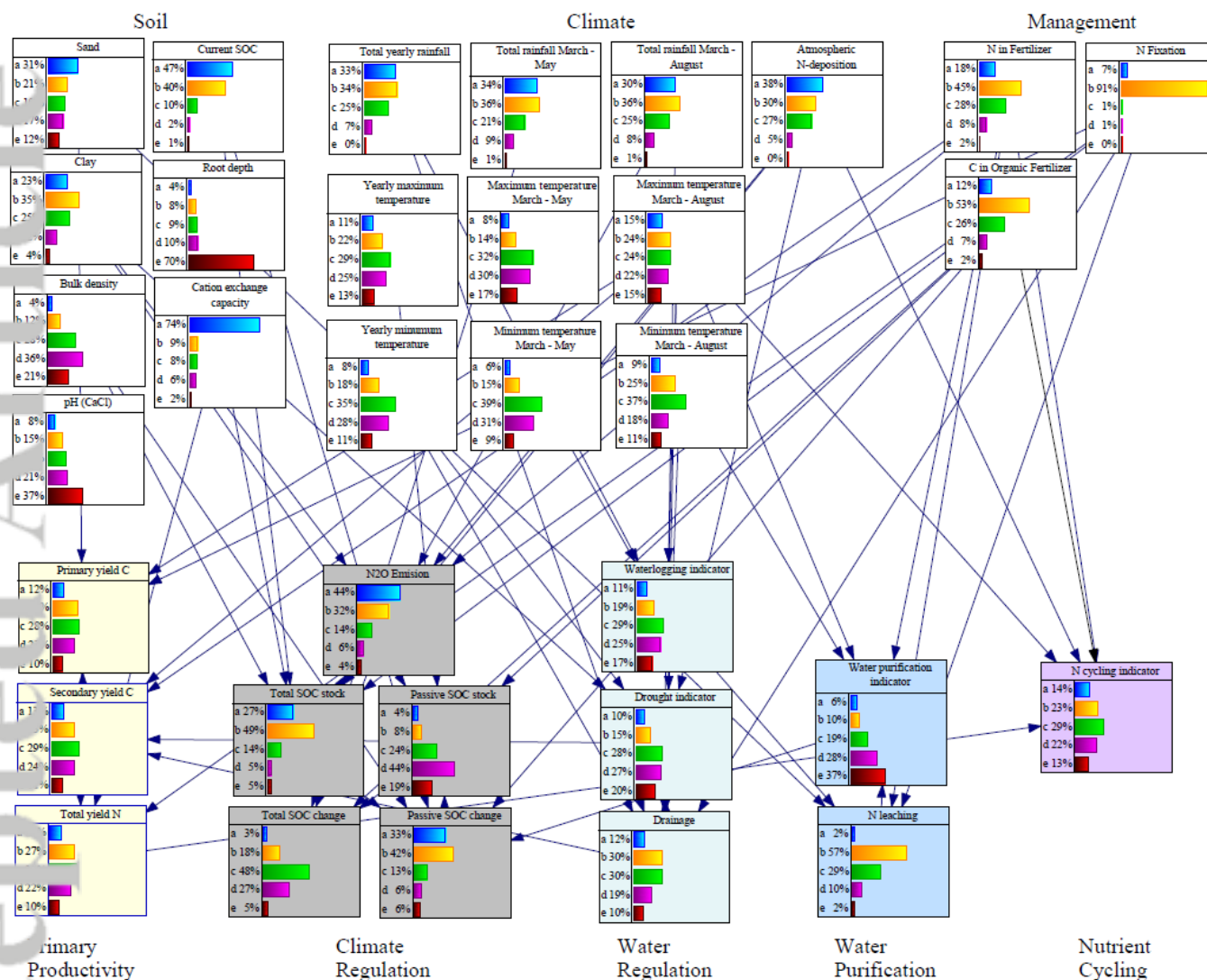
Soil function	Indicator	Unit
Primary productivity	Primary Yield - C	g C / (m ² * year)
	Secondary Yield - C	g C / (m ² * year)
	Total Yield - N	g N / (m ² * year)
Carbon sequestration and regulation	N ₂ O Emission	g N / (m ² * year)
	Total SOC stock	g C / m ²
	Total SOC change	g C / (m ² * year)
	Passive SOC stock	g C / m ²
	Passive SOC change	g C / (m ² * year)
Water regulation	Waterlogging indicator	days / year
	Drought indicator	days / year
	Drainage	mm
Water purification	Water purification indicator	ratio
	N Leaching	g N / (m ² * year)
Provision and cycling of nutrients	N-Cycling Indicator	ratio

Connections which were removed after review:

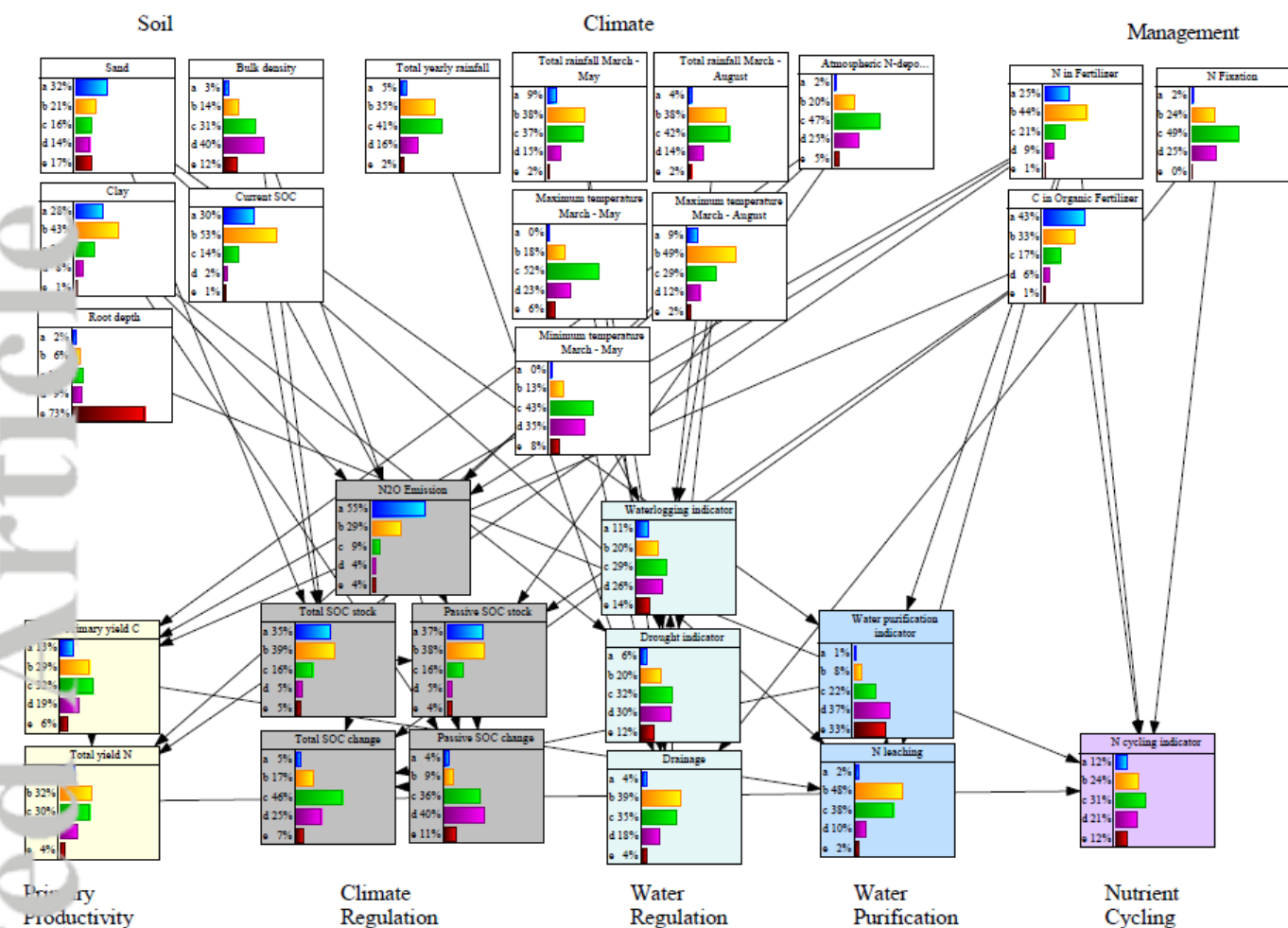
- N₂O – Passive SOC
- Change passive SOC – N Cycling Indicator
- Passive SOC – Water purification indicator

Acyclic directed graphs (DAC) of the different crop BNs with the probability distributions are given. Explaining variables (white) are grouped according to their characteristics in the upper part of the graph, soil function variables and indicators are grouped according to the soil functions in the lower part.

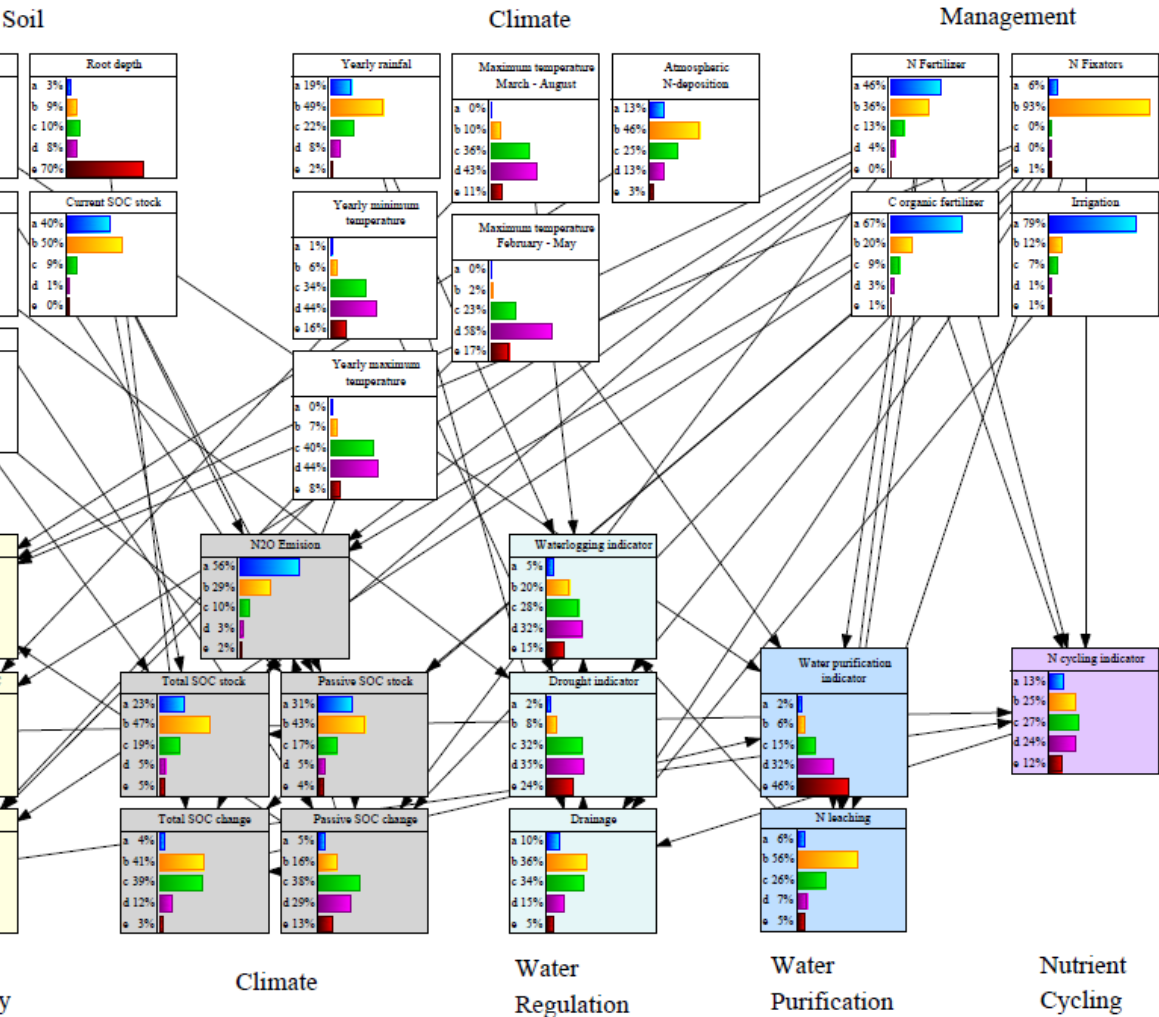
Barley



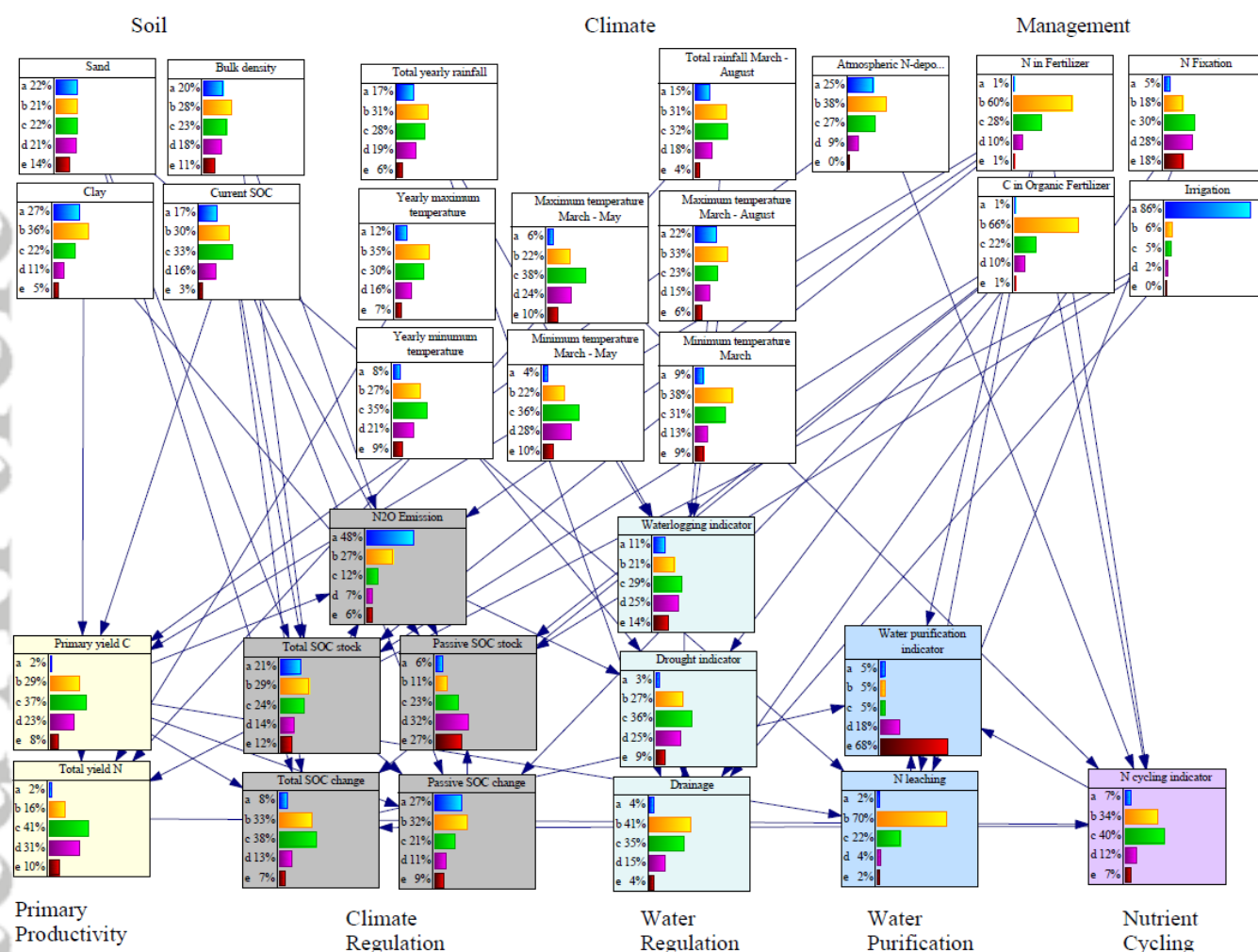
Silage maize



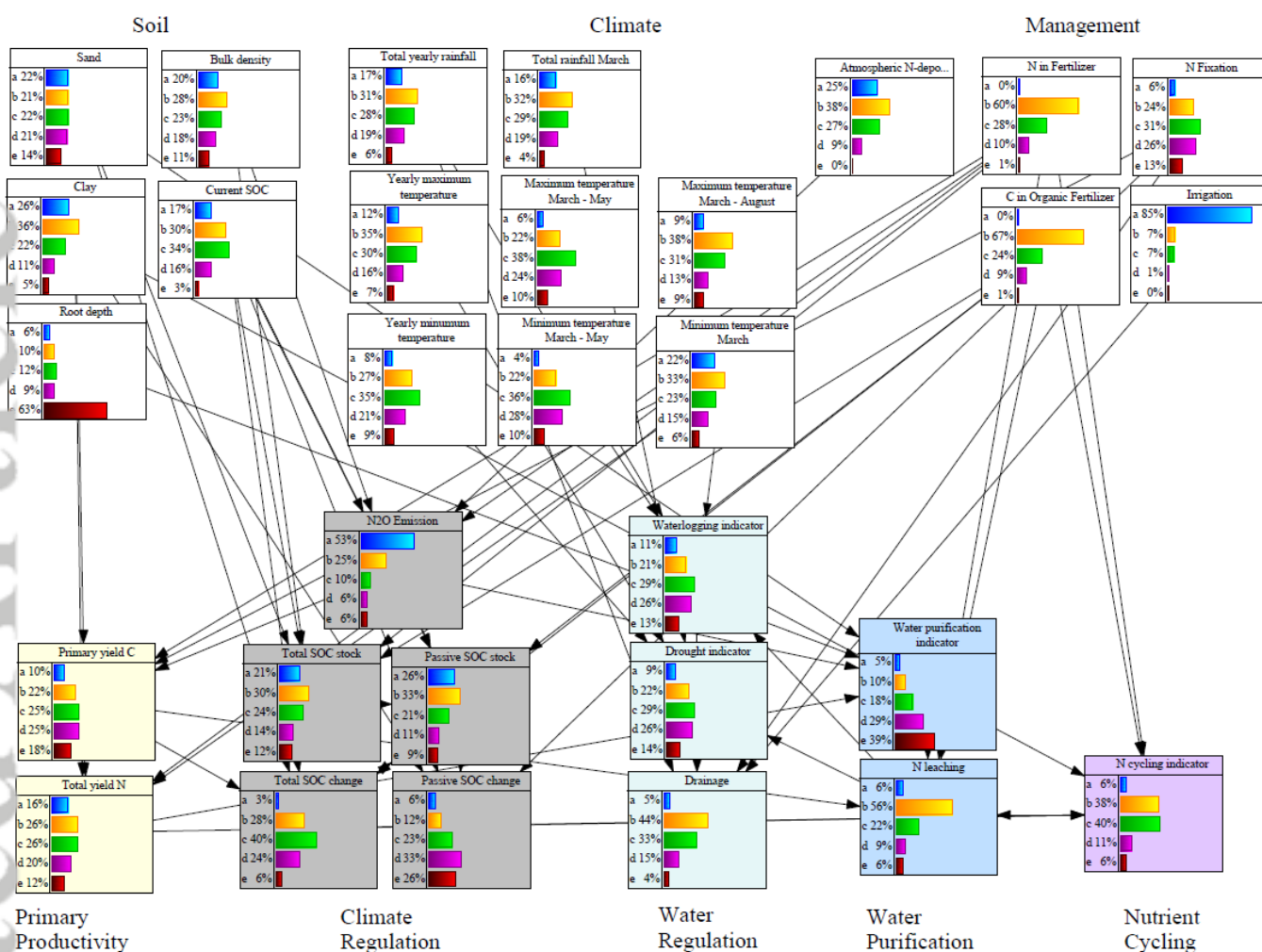
Grain maize



Intensive grasslands – hay

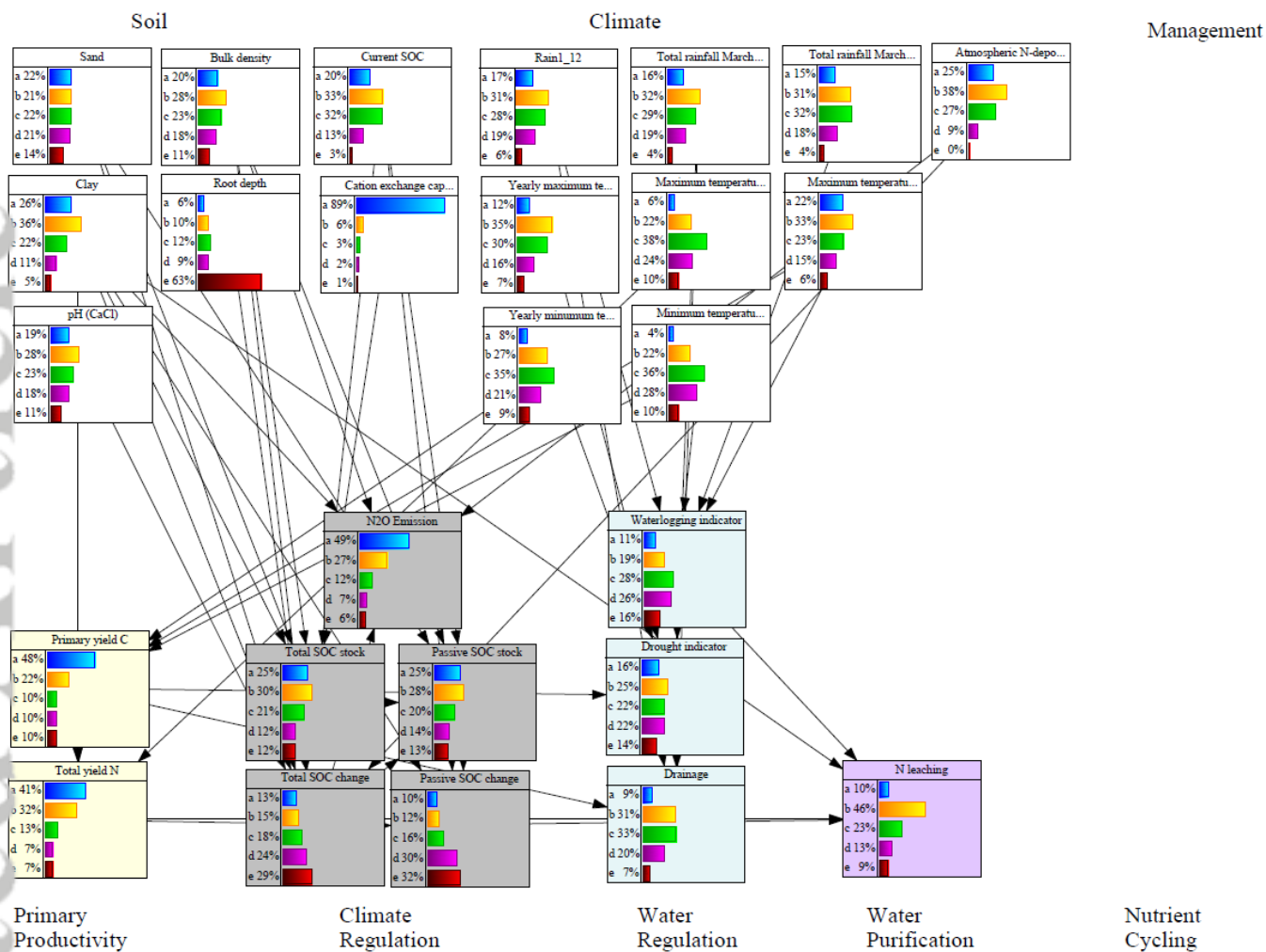


Intensive grasslands – grazed

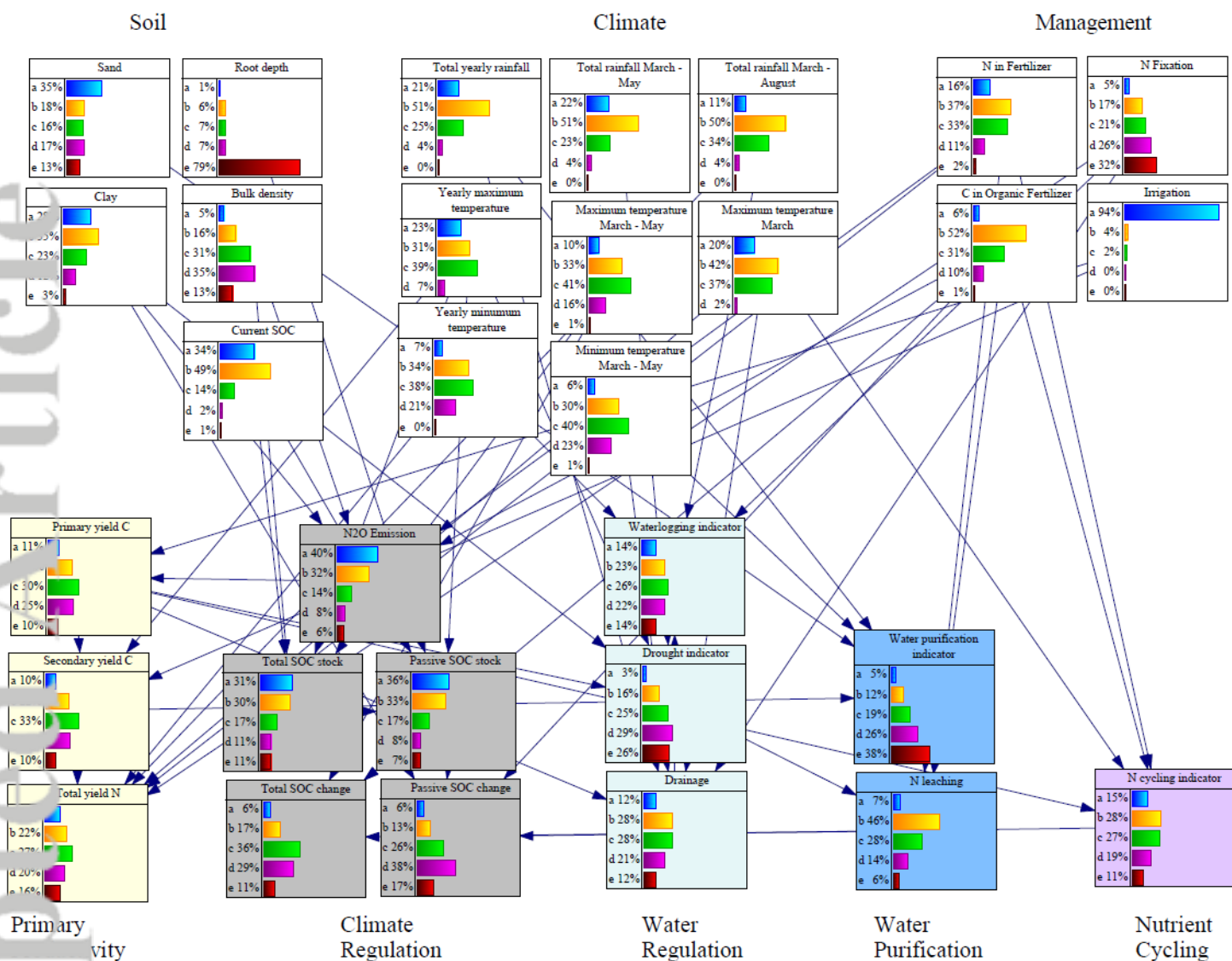


Extensive grasslands – grazed

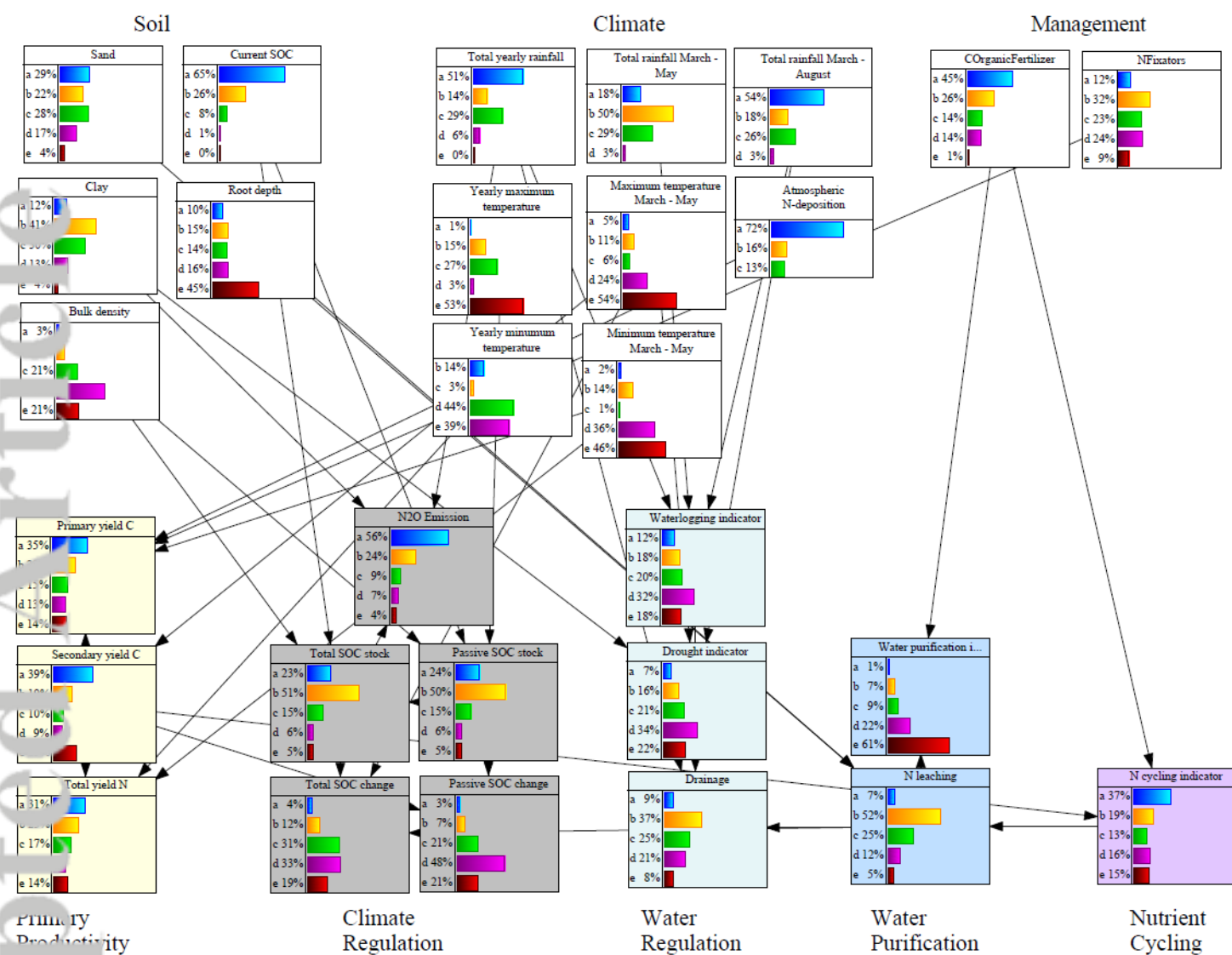
Accepted Article



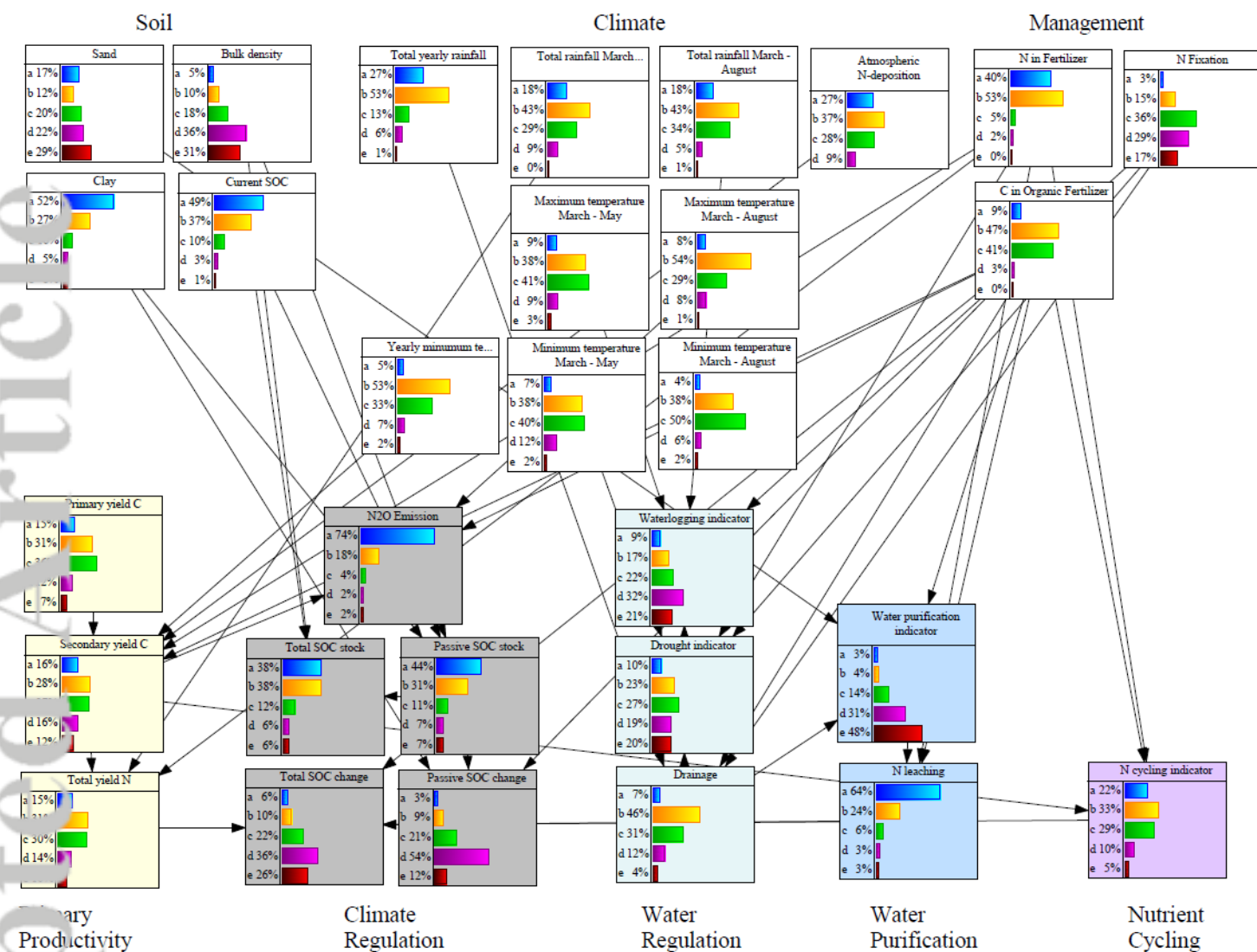
Rapeseed

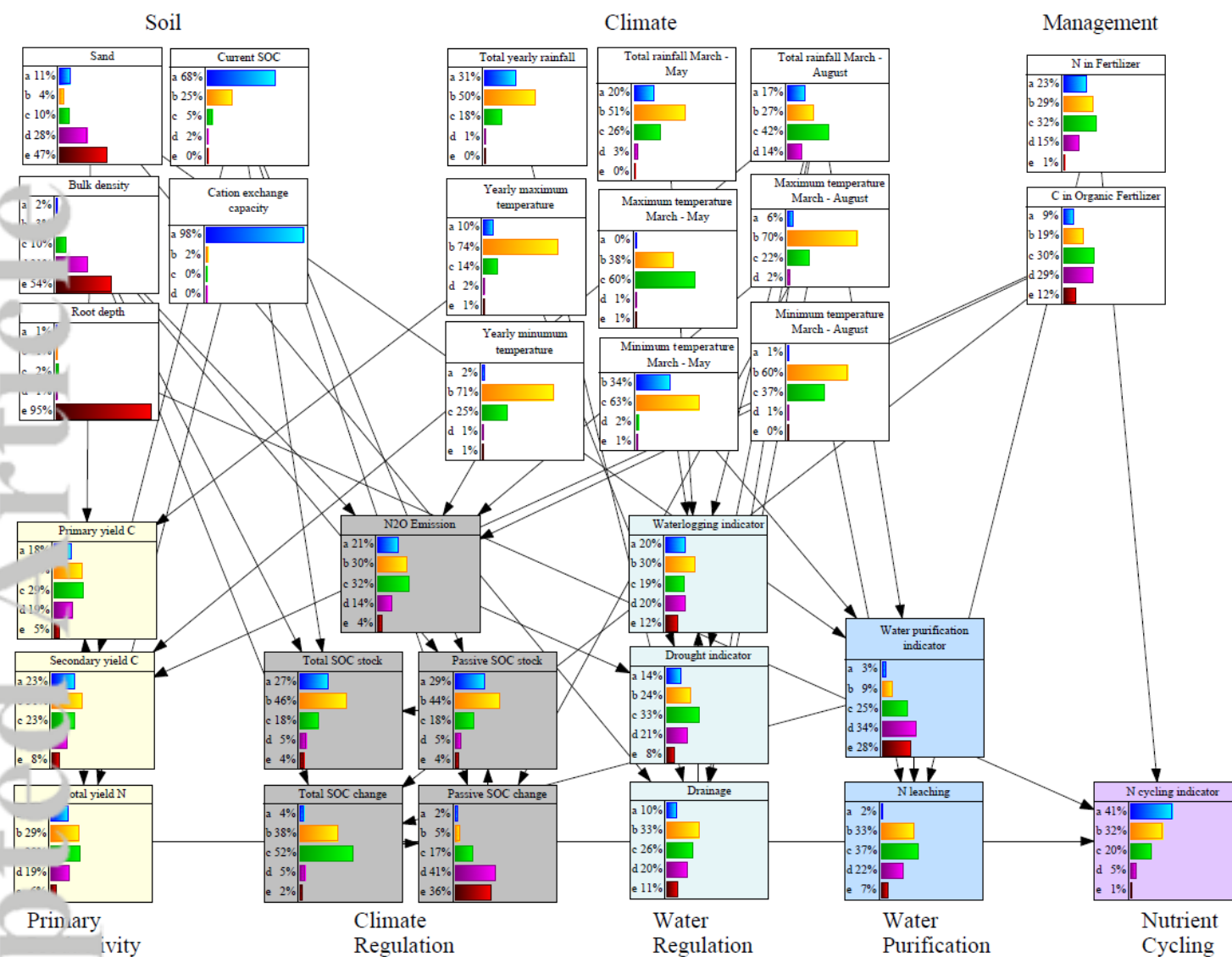


Peas

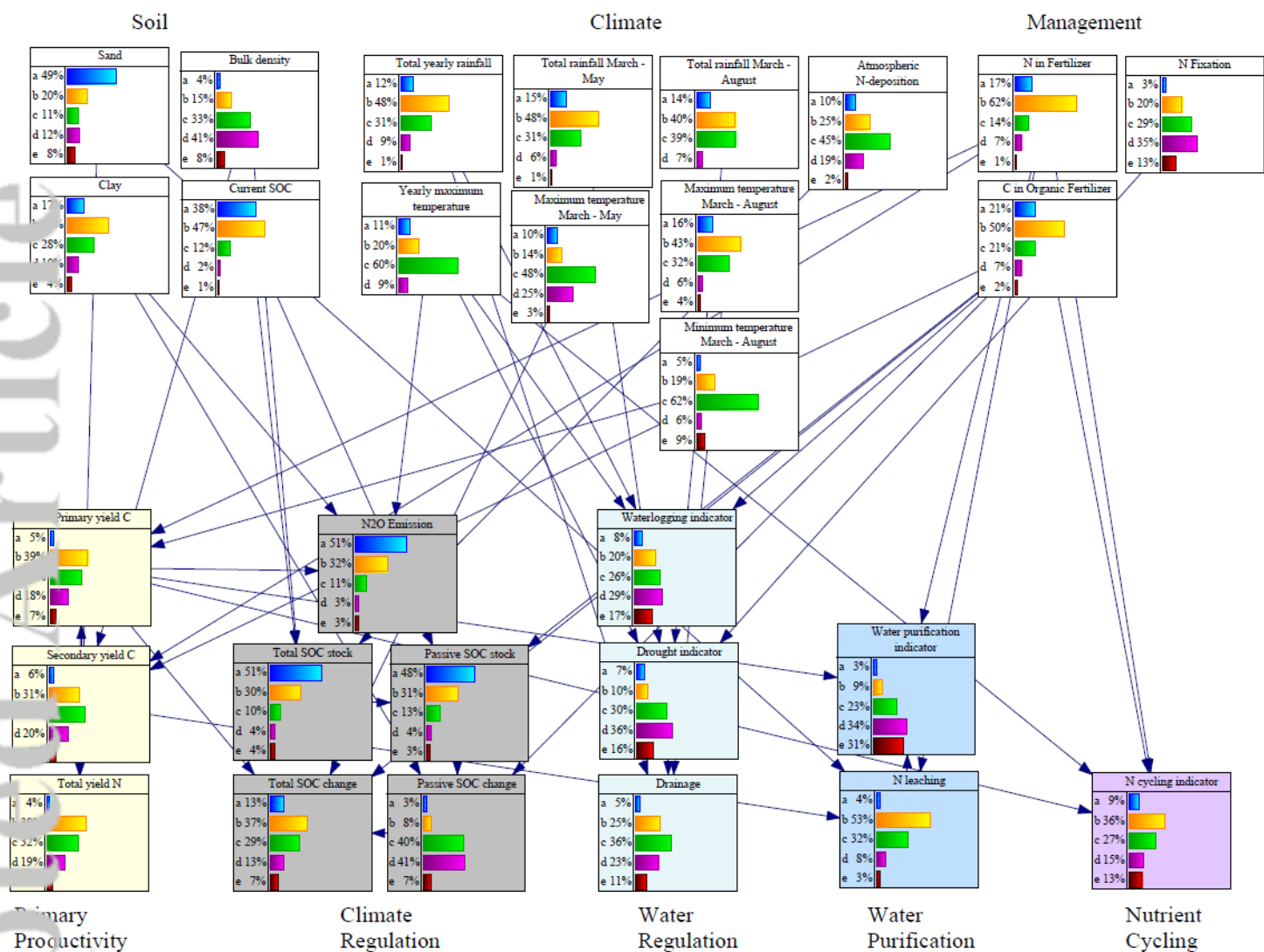


Potato

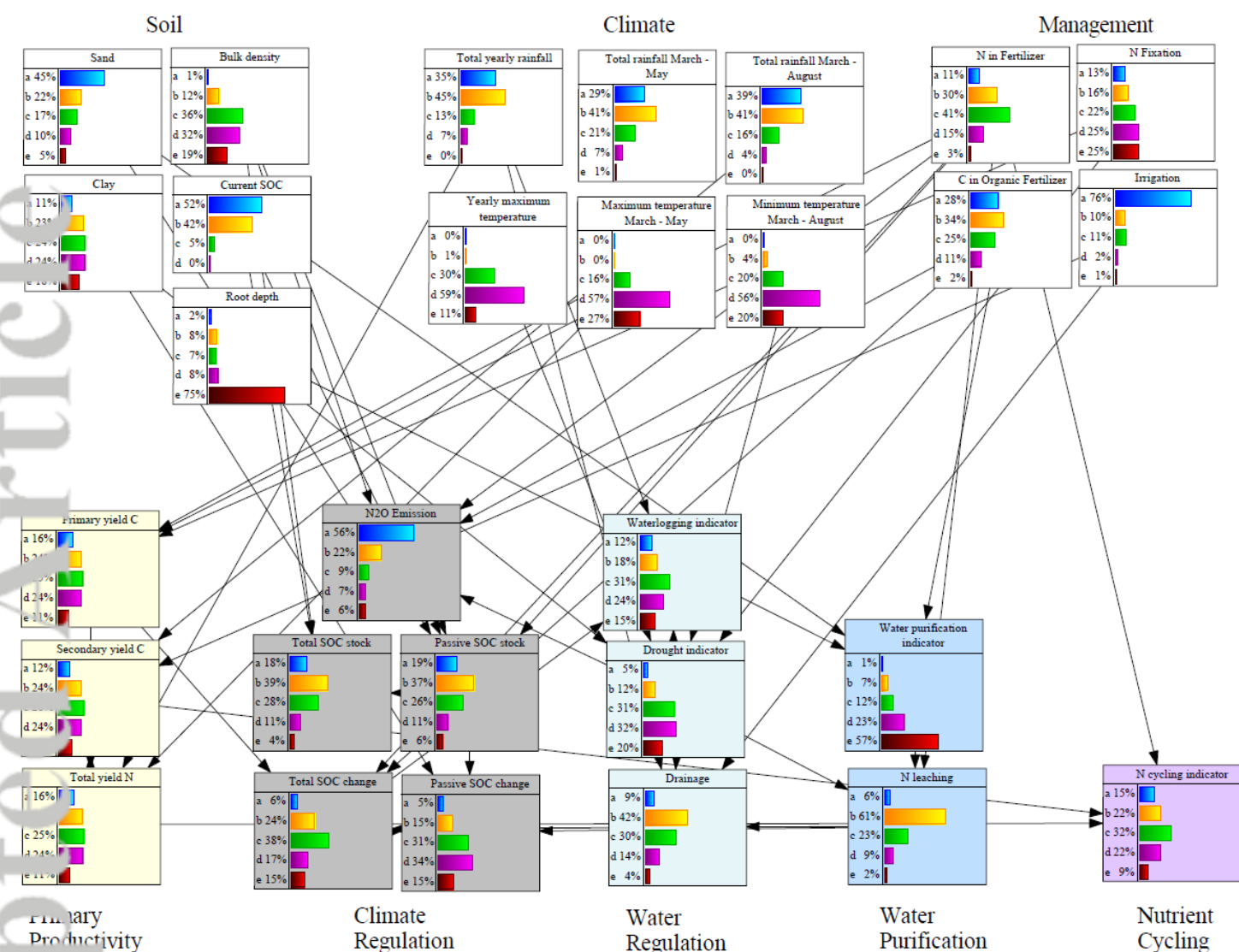




Sugar beet

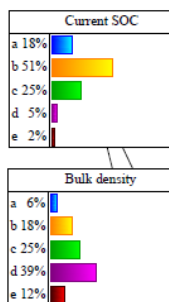


Sunflower

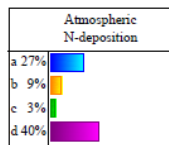
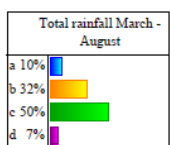
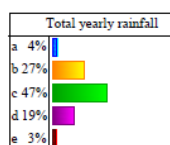


Spring wheat

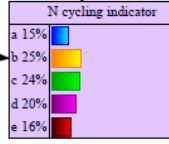
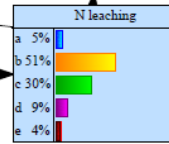
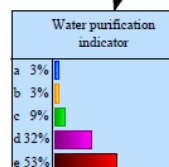
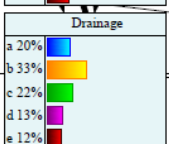
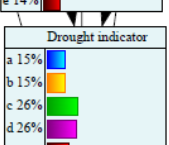
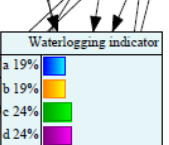
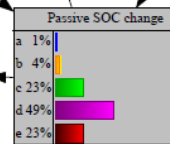
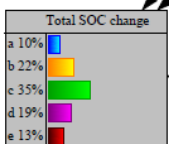
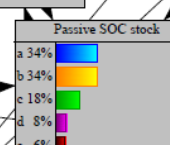
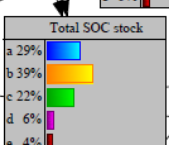
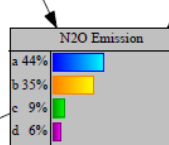
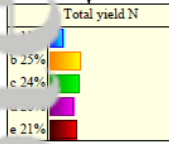
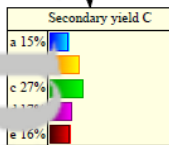
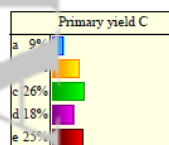
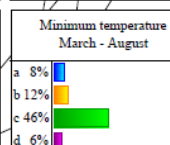
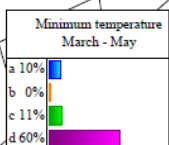
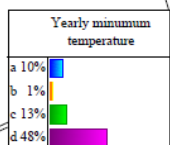
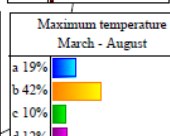
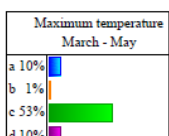
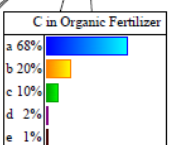
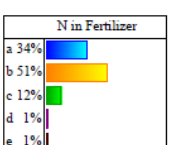
Soil



Climate



Management



Primary Productivity

Climate Regulation

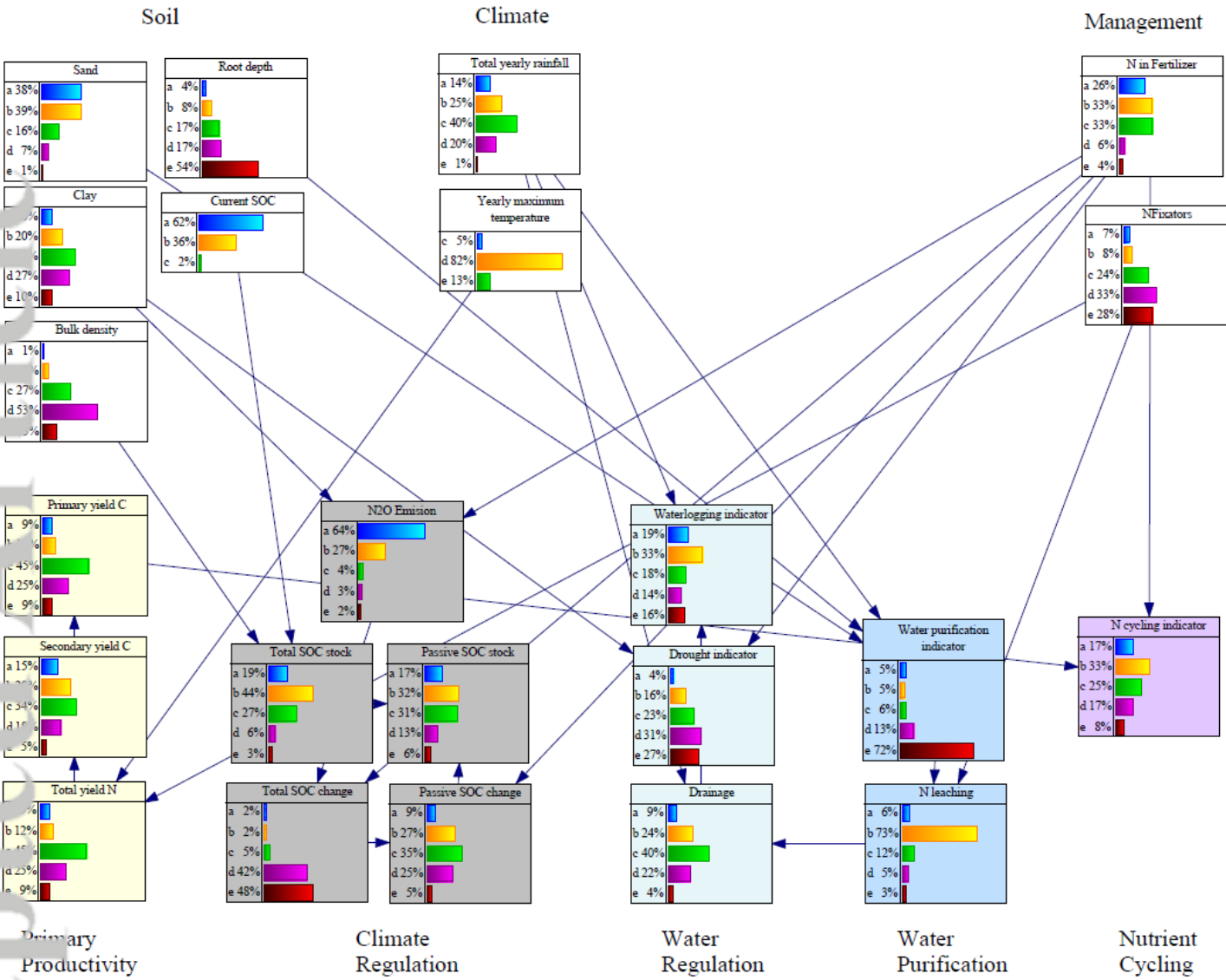
Water Regulation

Water Purification

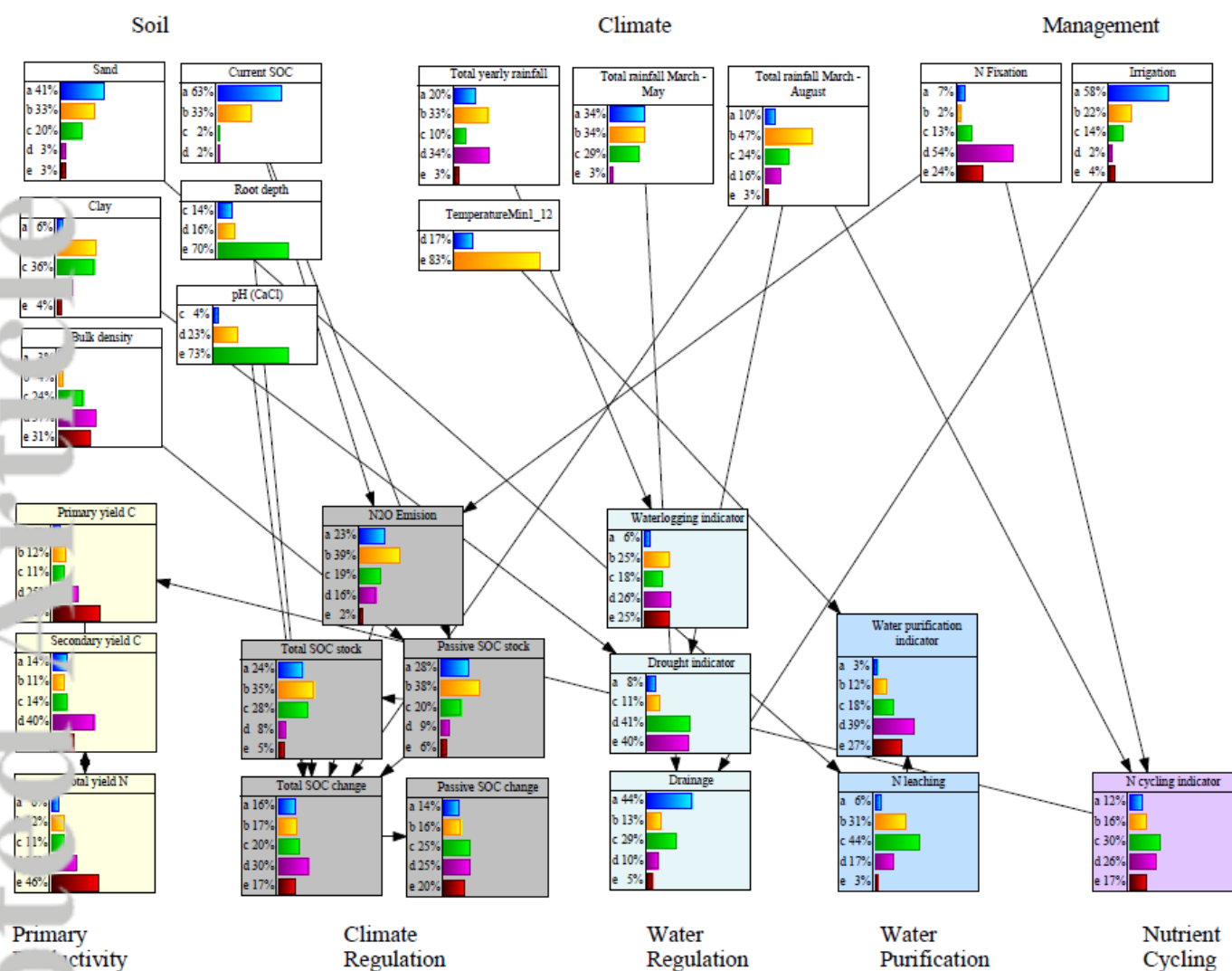
Nutrient Cycling

Spring durum wheat

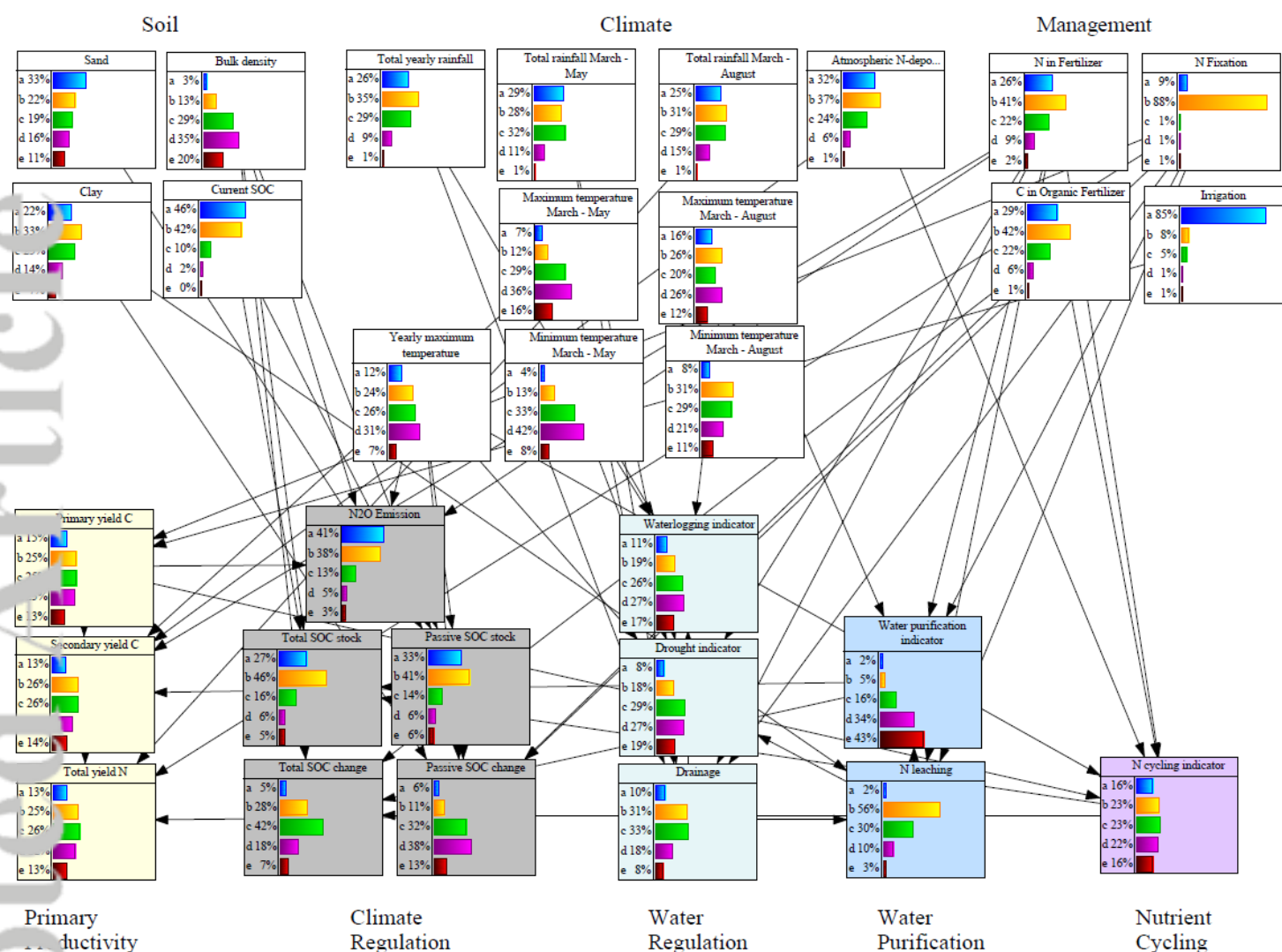
Accepted Article



Soybean

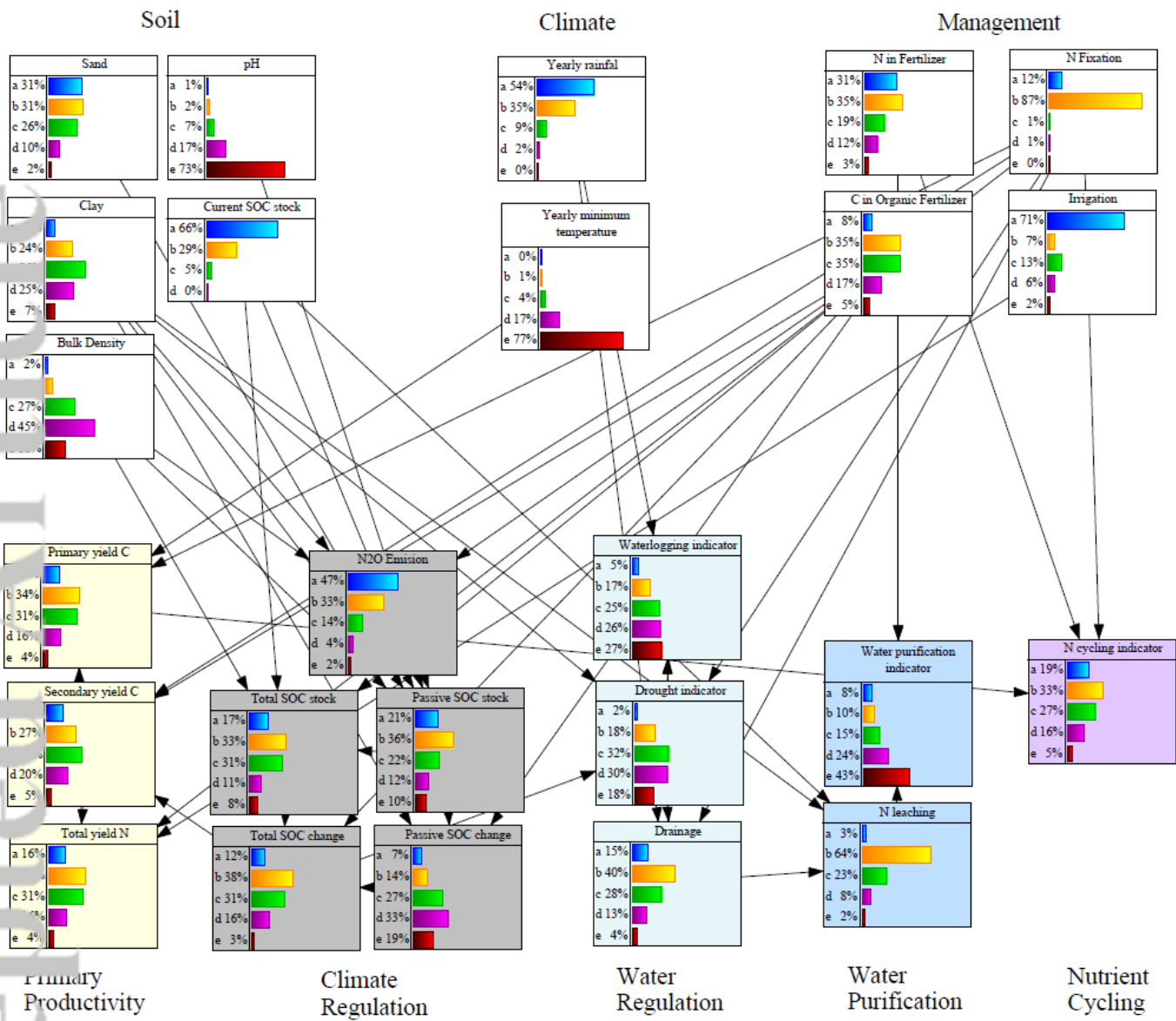


Wheat



Durum wheat

Accepted Article



Addendum C: Mean, median and standard deviations for each of the z-score changes under the different maximization scenarios as presented in Figure 5.

Maximization _ PP			
Function	mean	median	sd
PP	0.975	0.596	1.043
CR	-0.057	-0.061	0.793
DR	-0.058	-0.034	0.400
WL	0.100	0.075	0.905
WP	0.037	-0.020	0.625
NC	0.075	0.047	0.281

Maximization CR			
Function	mean	median	sd
PP	-0.006	-0.002	0.408
CR	1.193	1.075	0.917
DR	0.034	0.000	0.446
WL	0.092	0.075	0.930
WP	0.168	0.006	0.658
NC	-0.035	-0.007	0.307

Maximization DR			
Function	mean	median	sd
PP	0.154	0.087	0.399
CR	0.126	0.000	0.698
DR	1.488	1.412	0.824
WL	0.041	-0.005	1.049
WP	0.189	-0.002	0.684
NC	-0.007	-0.009	0.247

Maximization WL			
Function	mean	median	sd
PP	0.090	0.000	0.427
CR	0.382	0.200	0.883
DR	-0.029	-0.039	0.382
WL	5.315	5.558	1.207
WP	0.323	-0.001	0.935
NC	-0.059	-0.027	0.208

Maximization WP			
Function	mean	median	sd
PP	0.143	0.042	0.438
CR	0.378	0.223	0.744
DR	0.050	0.000	0.374
WL	0.132	0.075	0.952
WP	0.779	0.313	1.143
NC	-0.004	0.012	0.234

Maximization NC			
Function	mean	median	sd
PP	0.304	0.176	0.475
CR	0.088	-0.012	0.724
DR	0.028	0.000	0.391
WL	0.057	0.075	0.963
WP	-0.088	-0.007	0.571
NC	1.223	0.892	0.853

Detailed maps of current supply.

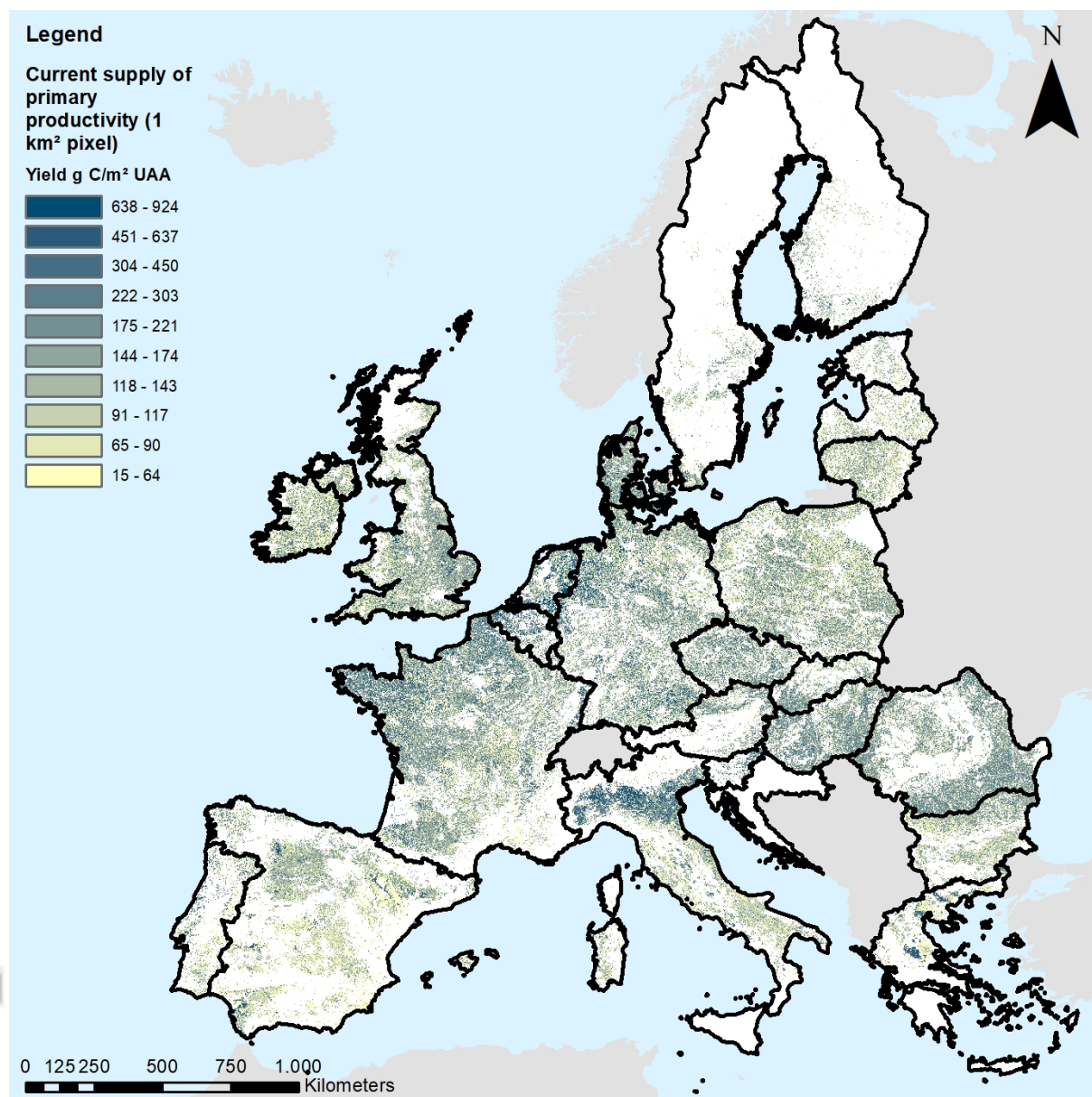


Figure 1: Current supply of primary productivity, expressed as the amount of carbon which can be harvested each year.

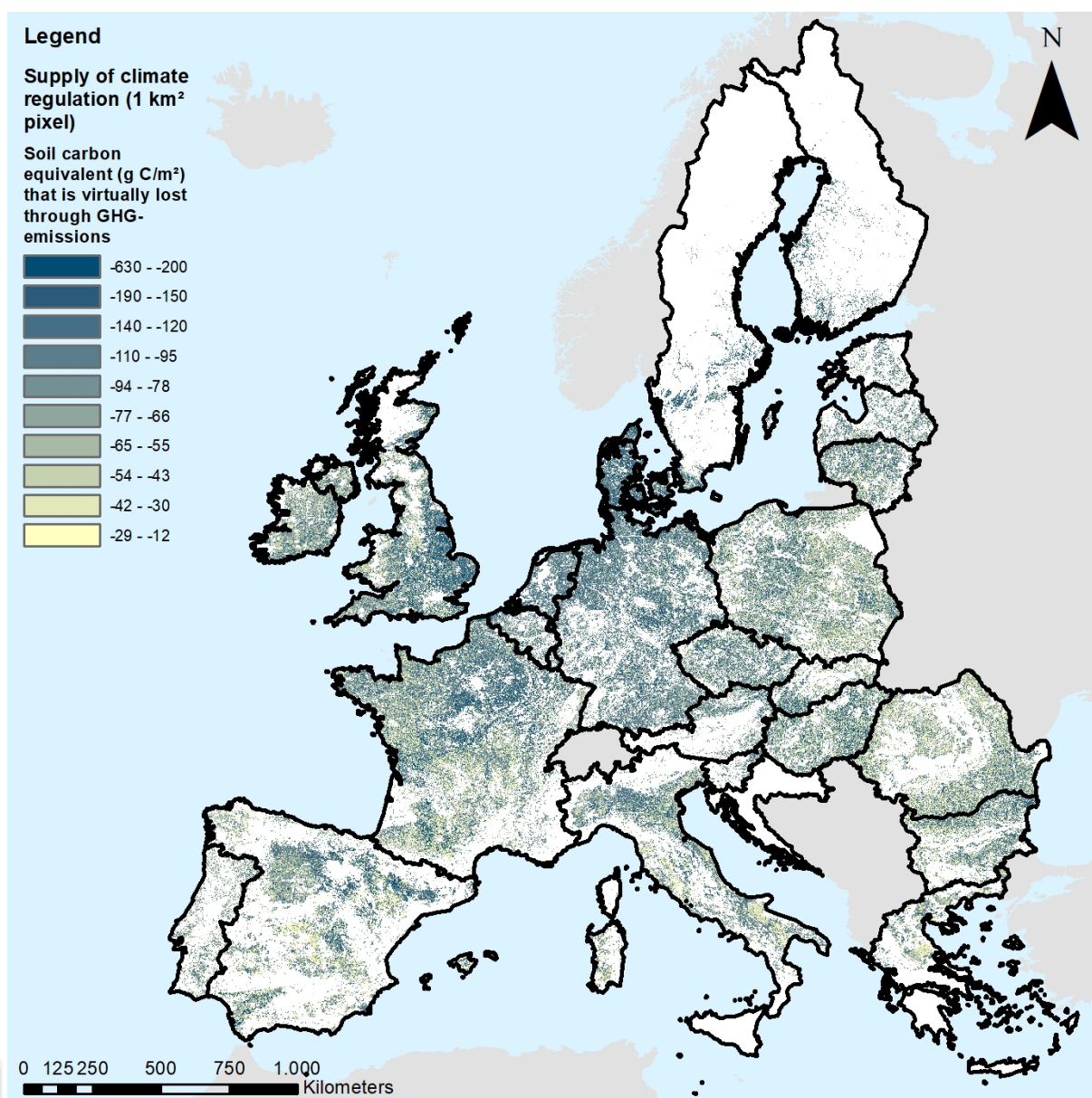


Figure 2: Current supply of climate regulation, expressed as CO₂-equivalent emissions from the soil each year.

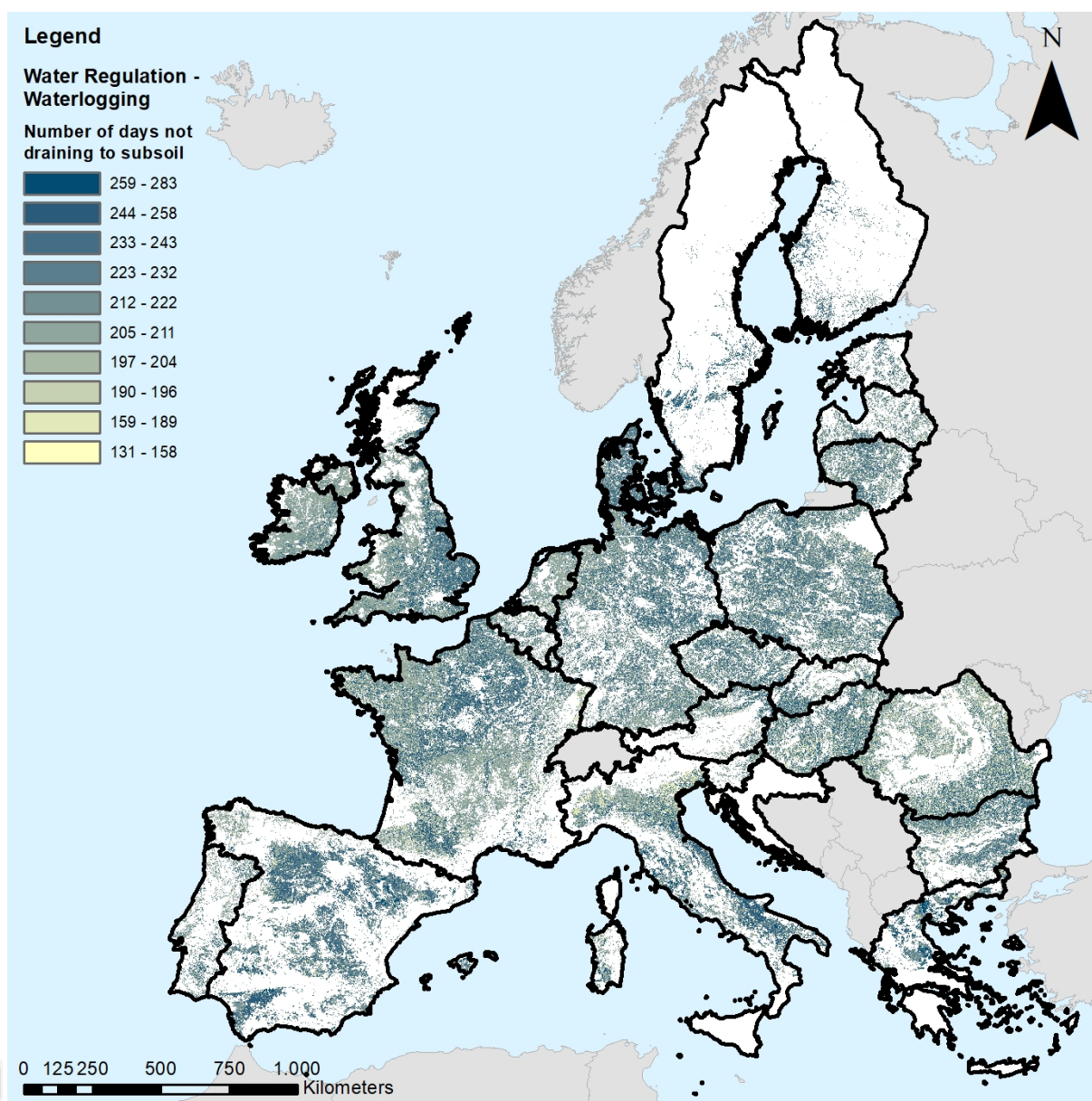


Figure 3: Current supply of water regulation, expressed as the number of days the soil is too wet.

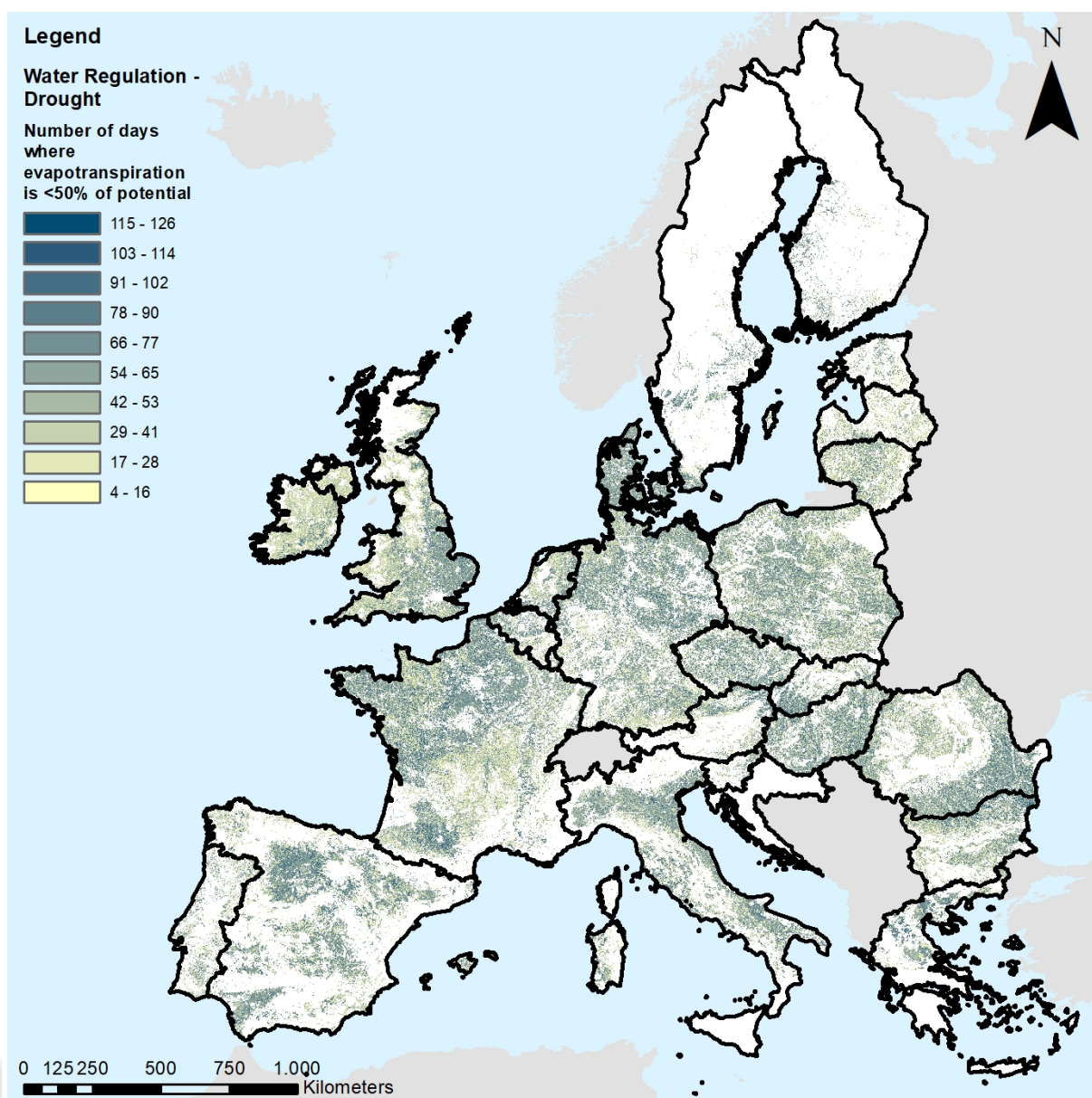


Figure 4: Current supply of water regulation, expressed as the number of days the soil is too dry each year.

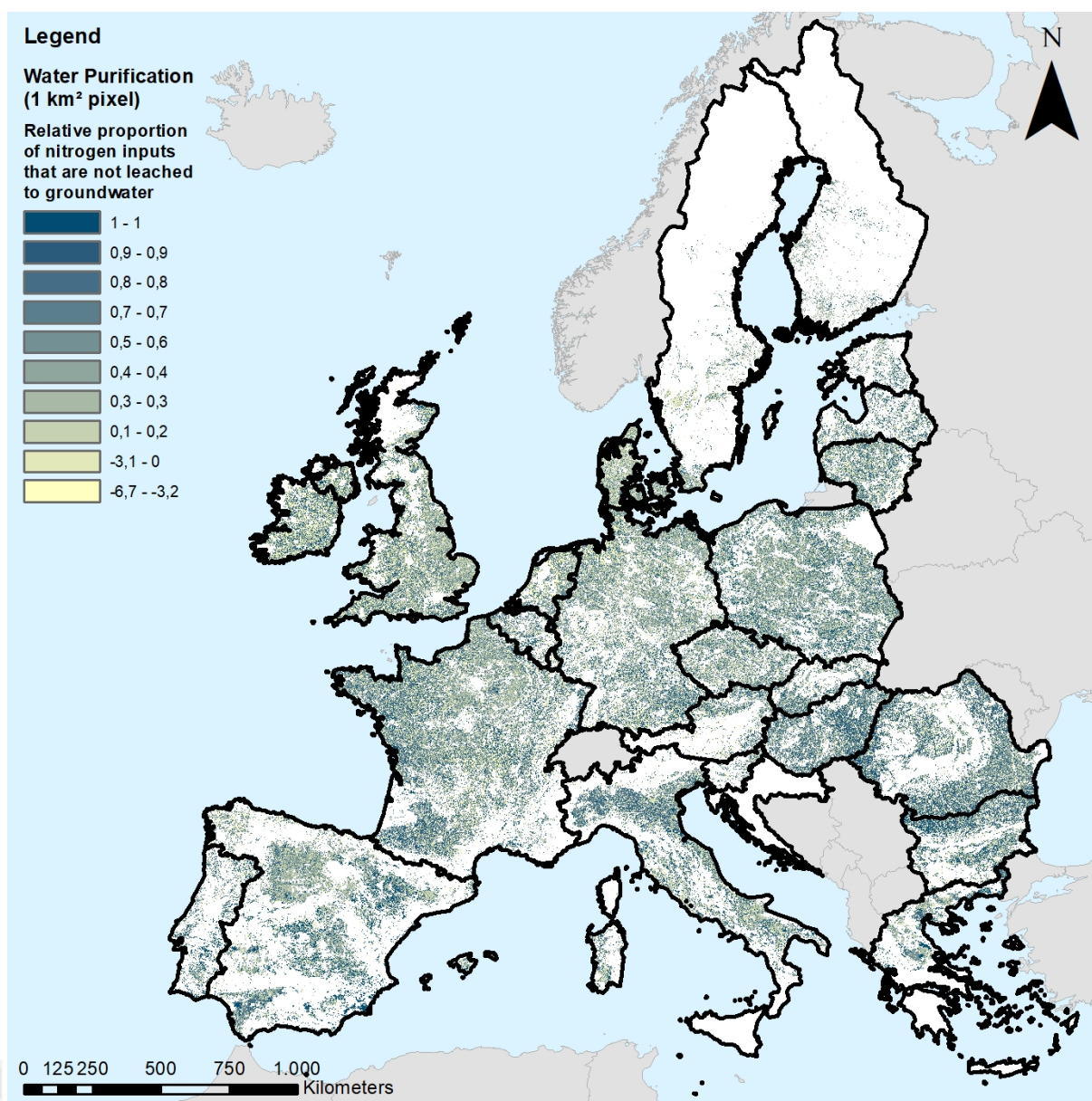


Figure 5: Current supply of water purification, expressed as the ratio between the amount of nitrogen (N) that is provided to the soil through different factors (fertilizer, aerial deposition and N-fixators) and the amount of N that is released towards the ground water each year.

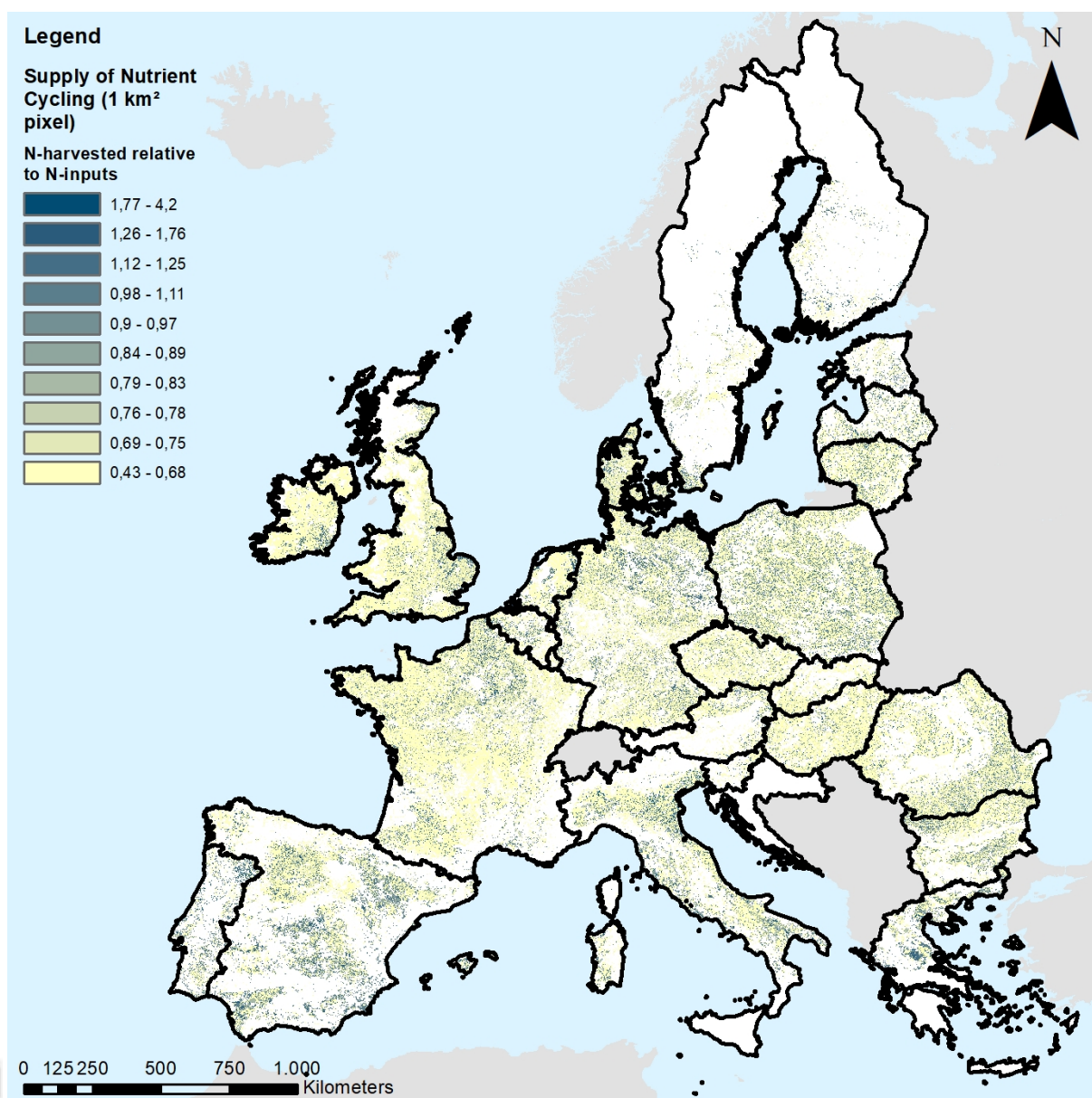


Figure 6: Current supply of nutrient cycling, expressed as the ratio between the amount of N that is harvested and the amount of nitrogen that is provided to the soil through different factors each year.